The Role of Security Analysts in the Emergence of New Technologies: The Case of Internet Firms

by

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Dedication

To my grandmother, Visalakshi Kunapuli, who taught me the love of learning.

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Abstract

I examine how information intermediaries' prior experience or status influence the complexity of their evaluations in the context of a new technological industry. Drawing from research on managerial cognition, I argue that analysts with prior experience or status engage in schematic information processing that affects the complexity of their evaluations. Further, I develop the construct of *evaluative complexity*, which is an indicator of comprehensiveness of analyst evaluations. Historical data from the early internet industry (from 1995 to 2005) of approximately 1800 analyst reports on the initial public offerings in the internet industry support my predictions that analysts with either prior experience or status demonstrate less complexity in their evaluations of internet firms. Specifically, in new market contexts experienced or high-status analysts are more likely to include less firm-specific information, convey more certainty in a context that calls for caution and are more likely to assess new technological firms from unitary perspectives. Analysts with My research aims to contribute to our understanding of the role of infomediaries in the emergence of new technologies and the paradox of experience and status in new market contexts.

Chapter 1 Introduction

Technological change and innovation are of central importance to both strategy researchers and practitioners (e.g., Henderson and Clark, 1990; Tushman and Anderson, 1986). A substantial body of research examines the behavioral and cognitive factors of firms and their stakeholders that influence technological change in incumbent organizations (Tripsas and Gavetti, 2000; Benner and Tushman, 2002; Eggers, 2012; Benner, 2010; Benner and Ranganathan, 2012). While this research has found that external stakeholders, such as security analysts, tend to impede new technological strategy implementation in incumbent firms, there has been lesser focus on how security analysts influence the emergence of a new technological category.

This is an important gap that merits attention because security analysts—as central information intermediaries—play a key role in new technological evolution. As Aldrich and Fiol (1994) point out, issues of legitimacy and information asymmetry are compounded in new market contexts. And in precisely these contexts, security analysts can provide information on firms adopting new technologies to a wider audience such as media, investors, and end customers. Other information intermediaries, such as media and critics, often rely on analysts' reports to provide information on the new technologies to the end audience (Brauer and Wiersema, 2018).

Furthermore, there is considerable evidence in extant literature that security analysts' coverage of new firms in established industries helps them acquire important financial and non-financial resources (Cliff and Denis, 2004; Pollock and Gulati, 2007). Firms that do not receive analyst coverage suffer an “illegitimacy discount” that affects their stock market success (Zuckerman, 1999). Extending these arguments to the context of new markets, security analysts could play an even more prominent role in drawing investor attention not only to the new firms, but also to the new technological category.

New technologies are often based on novel scientific principles that fundamentally alter industry structure, the products within, and their applications (Schumpeter, 1942; Henderson and Clark, 1990). Audiences make sense of these new technologies through interactions with producers (Rosa et al., 1999: 64), which help them understand the novelty of the new technology. Analysts facilitate this process by providing stories (Wansleben, 2012), narratives (Damodaran, 2017), or frames (Beunza and Garud, 2007). These presentations shape audience perceptions and interpretations of new technologies, thus influencing the legitimacy of the new technological category (Navis and Glynn, 2010).

To understand how security analysts, as external institutional stakeholders, might influence the emergence of new technology categories, I examine the cognitive underpinnings of analysts’ evaluations in the context of a new industry category. More specifically, I consider how a security analyst’s previous experience and status influence the *evaluative complexity* of their evaluations (i.e., the ability to provide an in-depth analysis of the new technology, while considering multiple informational viewpoints) of the emerging category. Evaluative complexity, rooted in the concept of cognitive complexity (Bieri, 1955), is particularly germane to understanding analyst evaluations in the context of new technologies because it reflects how actors gather and process information. Actors low on evaluative complexity tend to rely on heuristics, simplistic and stereo-typical information processing, while actors high on evaluative complexity rely on rely on data and consider a wide variety of perspective in inform their decision making (Graf-Vlachy, Bundy, and Hambrick, 2020). In the realm of new industries, in-depth evaluations can be crucial to help convey a new technology's novelty and what distinguishes it from existing technologies.

Drawing from the behavioral theory of the firm, I argue that previous experience or status influence the evaluative complexity of an analyst's reports. Studies have shown that boundedly rational actors develop cognitive schemas—i.e., knowledge structures that contain categories of information and relationships among them (Bingham and Kahl, 2013)—to gain efficiency in information processing (Walsh, 1995). Further, as actors gain experience in a particular domain, they often develop increasingly inflexible cognitive schemas that are more resistant to change (Dane, 2010). As a result of this cognitive inertia, actors can be slow to "revise their mental models… sufficiently quickly to adapt successfully to the changing environment" (Hodgkinson, 1997).

I build on these findings to argue that experienced analysts, when evaluating nascent firms in new technological categories, are more likely to draw from their prior cognitive schemas, developed through experiences following a different industry. Similarly, I argue that analysts who were conferred with high-status prior to following firms in a new technological category will rely on evaluative schemas that they perceive led to the high status. Hence high-status analysts are likely to use evaluative schemas better suited to an established industry when evaluating firms in a nascent industry. I predict that analysts with previous experience or status are more likely to be simplistic in their evaluations of firms adopting a new technology.

Using the internet industry as my research context, and approximately 1800 analyst reports published between 1995 and 2005, I examine the evaluative complexity of analysts' reports on internet firms. The advent of the internet in the mid-1990s was heralded as a transformational technological breakthrough that was significantly different from previous communication technologies (Abbate, 2001). It is thus an ideal context to study how analysts' prior experience and status shape their understanding of a new breakthrough technology. Furthermore, the high number of internet IPOs created a unique context in which a wide range of analysts—both experienced and inexperienced, high-status and low-status—were following the industry from its nascent stage.

To conduct this research, I collected analyst reports from ThomsonOne database and analyst measures, including experience, from I/B/E/S. A total of 665 analysts followed internet firms between 1995 and 2005, with an average experience of ~8 years; in my sample, 23% of the analysts achieved high-status before following an internet firm. Results of ordinary least-squared regressions, with IPO-firm and analyst control variables, support my hypotheses that experienced analysts are simplistic in their evaluations of firms in a new industry. Novice analysts, on the other hand, are more complex in their evaluations. To interpret the results of the quantitative analyses and to address specific alternative explanations of the effect of experience on evaluative complexity, and to understand whether complex analyst reports are useful to investors in their investment decisions, I also conducted interviews with buy-side analysts. The interviews confirmed that buy-side analysts rely on sell-side research to make sense of new technologies and their applications. Further, they find comprehensive and nuanced analysis, cautionary rhetoric, and information about firm specific strengths in sell-side research more valuable than cursory relaying of data.

This research contributes to research on cognitive perspectives on new technological emergence (Tripsas, 2009; Benner, 2010). Specifically, the study shows that analysts' previous experience and status could be constraining their evaluations of new firms based in novel technologies. Although research in accounting has mainly shown that prior experience improves the accuracy of an analyst's evaluations (e.g., Clement, 1999), I adopt a behavioral theory lens to show that experienced analysts might be cursory in their evaluations of new technological firms. In the context of a new technology, applying prior accumulated knowledge can lead analysts to make over-simplistic evaluations. Counterintuitively, inexperienced analysts might be more detailed in their evaluations as they depend more on context-related information to evaluate firms in new markets. This study also shows a potential downside of high-status analysts, as status conferral might lead to inflexibility in evaluations of firms in new technological industries.

This work also advances our understanding of analyst assessments by introducing a novel tool—evaluative complexity—to study the comprehensiveness of analyst evaluations. Management research on security analysts has primarily focused on their recommendations and ratings. At the same time, prior research has also shown that investors pay lesser attention to analyst recommendations (Buenza and Garud, 2007) and focus more on the rationale behind the recommendations. The construct of evaluative complexity enables us to understand the structure and content of analyst evaluations and how analysts following the same industry can differ in the comprehensiveness of their evaluations.

While prior work on analyst evaluations has assumed that evaluative schemas are uniform across analysts following an industry, this research shows that analysts can differ in the composition and application of schemas, especially in the nascent stages of industry evolution. Examining the evaluative complexity of analysts' discourse helps us understand how these important external institutional actors vary in their rationale that supports their recommendations. Evaluations high on evaluative complexity provide a nuanced understanding of the new technology, incorporating information from multiple perspectives and specifying firm-specific strengths in adopting the new technology. Further, as intermediaries' evaluative schemas focus stakeholder attention and actions (Becker, 2008), comprehensive evaluations can help investors understand the distinctive features of the new technology in comparison with existing technologies.

Finally, studying the impact of analysts' prior histories also extends our understanding of how organizational actors make decisions under uncertainty. This study provides a possible explanation for why actors may vary in their responses to uncertain contexts. Analysts with prior experience or status fall back on their previous schemas in uncertain new industry contexts. Depending on their prior histories, actors might have differential responses to uncertainty in new market contexts as reflected in the complexity of their justifications. Analysts' responses to uncertain environments, such as new market contexts, have important implications for how they interpret and pay attention to the firms in these new markets. As analysts play an important role in reducing the information asymmetry of new markets, the complexity and comprehensiveness of their justifications can shape audience perceptions of the novelty of new markets, thereby influencing cognitive legitimacy of these markets.

Chapter 2 Technological Change and Analysts' Evaluations

A substantial body of research examines organizational factors that contribute to technological change and the emergence of new technologies (Eggers, 2012; Benner and Ranganathan, 2012). While this research has mainly focused on firm-level behavioral and cognitive factors (Tripsas and Gavetti, 2000; Benner and Tushman, 2002), the influence of external actors, such as security analysts, is an emerging theme that extends the research beyond the firm boundaries. Numerous studies have shown that security analysts are important actors who influence firm strategies, including innovation strategies (Benner, 2010; Tripsas, 2009), through their evaluations and recommendations.

The extant research that examines the role of security analysts on innovation strategies (e.g., Benner and Ranganathan, 2012; He and Tian, 2013; Theeke, Polidoro, Fredrickson, 2018) focuses primarily on incumbent firms. It has found that security analysts' recommendations and ratings actually inhibit firms' investments in new technologies and, more specifically, that analysts lag behind incumbent firms in updating their evaluation criteria to suit the changed strategies (Benner, 2010). This research also finds that brokerage companies stop the coverage of firms following novel strategies because security analysts find it challenging to extend their existing evaluative routines to assess the incumbent firms' innovations (Theeke, Polidoro, Fredrickson, 2018). There is also evidence suggesting that analysts exert pressure on incumbent firms to meet short-term goals while forgoing long-term investments in innovative projects (He and Tian, 2013).

While these studies show that security analysts face difficulties in evaluations when incumbent firms change technological strategies, we do not know the cognitive difficulties that security analysts might face in the context of a new technological industry. Evaluating firms in new industry categories is a difficult task. Firstly, while criteria for evaluation are well formed in mature industries, such criteria are not yet established in nascent technologies. Indeed, in the initial stages of technological evolution, analysts often find it difficult to reach a consensus on the relative importance of different aspects of the new technology. For instance, Beunza and Garud (2007) document different types of interpretive frames that analysts associated with firms like Amazon in the early internet industry—these frames influenced analysts' categorization of these nascent firms, as well as their recommendations and outlook. Ultimately, analyst evaluative criteria help focus investor attention on specific aspects of the technology. And, as Hsu (2006) argues, in an evolving industry category, these criteria help shape which aspects of the new technology become accepted by the broader audience.

Second, these nascent firms often do not fit existing categories. The first question analysts ask when assessing a firm is "What type of firm is this?," so they can categorize the firm and apply category-specific evaluative criteria (Zuckerman, 1999). Novel technologies deviate from existing category definitions and are difficult to fit into existing categories. As the new category evolves, category definitions change—for instance, initially all dot-coms were categorized as internet firms, but more refined category definitions (software-as-a-service, e-commerce, etc.) evolved as more internet firms became public.

Thirdly, firms engaged in novel technologies might deviate from analysts' existing financial metrics. Firms in nascent industries are typically "growth stocks," i.e., firms that have revenues but no earnings or dividends (e.g., Benner and Ranganathan, 2012), hence analysts might not be able to use existing evaluation models to assess them. For example, firms like Uber, Airbnb, and Tesla do not fit into existing category definitions of taxi, hotel, and car industries respectively. These firms also have no positive profits, but investors are positive about their growth prospects (Damodaran, 2017). In such scenarios, security analysts try to provide narratives (Damodaran, 2017) or frames (Beunza and Garud, 2007) to help investors make sense of the new firms.

Historically, novel technologies often transformed existing industries by shifting knowledge bases and transforming business models, and thus changing the way organizations operated. Telephone, automobiles, airplanes, wireless telecommunications, and more recently autonomous vehicles and artificial intelligence are examples of radical innovations that transformed how organizations conducted business. Given that novel technologies occur regularly over the course of industry lifecycles, it is important to understand how security analysts approach and interpret these new technologies.

Novel Technologies as Category Emergence Story

This research agenda also aligns with the research on the socio-cognitive view of category emergence that examines the cognitive and institutional underpinnings of market exchanges (Zuckerman, 1999; Rosa et al., 1999; Hsu, 2006; Ruef and Patterson, 2009; Navis and Glynn, 2010; Negro, Koçak, and Hsu, 2010; Durand and Paolella, 2013; Vergne and Wry, 2014). In this view, "categories provide a cognitive infrastructure that enables evaluations of organizations and their products, drives expectations, and leads to material and symbolic exchanges" (Durand and Paolella, 2013: 1102). Recent research in this tradition began to move away from the conceptualization of categories as ex-ante given and of category boundaries as defined, toward a conceptualization of category emergence that is a result of agency, interactions, and shared understandings among actors in the social structure of markets (producers, audience, and intermediaries) (Durand and Khaire, 2017). Categories thus emerge as a result of sensemaking interactions between self-interested actors, working towards common meanings with regards to both products and processes. New category emergence involves developing shared socio-cognitive structures through narratives and discourses that help audiences distinguish between category members and outsiders (Durand and Khaire, 2017).

Information intermediaries, such as security analysts, are an important constituent in this social structure, as they enable sensemaking of new categories through their narratives and evaluations (Wansleben, 2012). In particular, security analysts help audiences to make sense of new technologies through their evaluative schemas that guide investor assessment of quality of firms and helps them rank the nascent firms within the new market category. Hsu (2006) argues that standards for quality of firms within a category do not arise from the inherent characteristics of the firms within the category, but rather are externally imposed by analysts and critics acting as category gatekeepers.

There is a distinct difference between how analysts assess the quality of firms in mature and nascent industry categories. In mature industry categories, the rules for assessing quality of category members—in particular the “categorical imperative” (Zuckerman, 1999) to conform to recognized and established prototypical characteristics—is well-defined. Category membership features are well-known, such that audiences have a clear understanding of products, processes, and business models of firms within the category. These shared rules and socio-cognitive structures help audiences compare firms in the category, demarcate category members into groups, and compare alternatives (Rosa et al., 1999). These established rules help intermediaries evaluate and assess firms, and discount firms that do not align with the categorical prototype (Zuckerman, 1999).

In nascent industry categories the rules to assess quality of firms are not well-defined, given that the emerging industry structure is still evolving. This presents an opportunity for analysts to develop schemas that they that they view as fitting the new category. Constructing evaluative schemas in the context of a new industry category has important implications not only for the analysts' careers but also for the legitimacy of the category members. When an analyst's narratives, frames, and evaluative schemas become widely accepted, they will be able to justify their contribution as gatekeepers for the emerging category. Such analysts would be considered experts on the new category by media and other external stakeholders. Thus, the context of a new industry category creates opportunities for security analysts to provide evaluative schemas that are seen as objective and that are accepted by other analysts and investors.

Analyst evaluative schemas contribute to the legitimacy of new industry categories through the rules of inclusion within the category, such that new category boundaries become clear in the minds of the audience. Evaluative schemas also shape the evolution of new technologies through their focus on certain aspects of the technology, while ignoring the other aspects. For instance, Beunza and Garud (2007) note that some analysts ignored the internet aspect of Amazon's IPO while highlighting its book-retailing business—thereby focusing investor attention on the retailing side of Amazon's offering.

In light of these discussions, it is important to examine how and why analysts' evaluative schemas vary in the context of a new technological category. Specifically, as research has shown that analysts' evaluations of incumbent firms undergoing technological change are influenced by their cognitive styles, it is imperative to understand the cognitive underpinnings of analysts' evaluations in the context of a new technological category.

Security analysts and Evaluations

Security analysts collect information on publicly traded firms and markets and provide recommendations, ratings, and information to investors. Based on the advice they provide, analysts can be of two types – sell-side and buy-side. Sell-side analysts are employed by brokerage firms and independent research firms and issue reports on an industry or a public company. The audience of these reports are institutional investors and buy-side analysts. Buy-side analysts provide advice for internal clients of proprietary portfolio or asset management divisions of banks funds and their research reports are not disseminated to outsiders. Most of the research in management literature focuses on sell-side security analysts (e.g. Benner and Ranganathan, 2012; Brauer and Wiersema, 2018; Zuckerman, 1999) as the sell-side reports are publicly available and the buy-side research is circulated within the proprietary funds.

Sell-side analysts are key information providers for investors and act as an informational bridge between firm management and their external stakeholders. As important institutional actors who engage with top management teams through earnings conference calls, analysts serve as an external governance mechanism to mitigate expropriation of shareholders by firm management (Jensen and Meckling, 1976). Analysts specialize by industry, typically following firms in one or two industries, in which they are considered to be experts (Brauer and Wiersema, 2018; Zuckerman, 1999).

While analysts are known to follow one or two industries at a given time, existing industries undergo technological discontinuities and new industries emerge based on new technologies. These changes in turn give rise to new industry categories. Daniel Reingold (Reingold and Reingold, 2014) was an all-star sell-side analyst covering the telecommunications industry in the early 1990s. He describes how brokerage firms recruited new analysts to follow the new industry category of telecommunications to "help investors figure it all out."

> Every time a new industry came along, Wall Street staffed up with analysts, traders, and bankers to cover it. …Wall Street desperately needed people who could help investors figure it all out. So in the early 1980s the Street went on a hiring binge, recruiting practically everyone it could find with experience in both financial analysis and the telecom sector…. (Reingold, 2014)

When new industry categories emerge, both experienced and novice analysts start following firms in the new industry category. Reingold highlights how, despite being an all-star analyst following the telecommunications industry, he missed the importance of the internet as a new and emerging technology:

> Jim Crowe (CEO of MFS and Level 3 Communications, both internet companies) was onto something new and important. Yet…I missed it entirely. He called it "IP," or Internet protocol, the new technology by which Internet information would flow through the world's communications networks. Crowe's notion was that the Internet was going to change the world, and that MFS would transmit much of the world's Internet traffic. … MFS had quietly acquired a small, relatively unknown company called UUNet (pronounced "you you net") for $2 billion. UUNet was the country's largest "Internet service provider" and was growing like wildfire. I was mystified. Although telecommunications and the Internet would later become as linked as Siamese twins, I didn't quite see the connection between the two. I made a mental note to someday figure

> out exactly what he was talking about. …But at the time, I was more concerned with surviving the next deal announcement... than I was with the largest technological shift of the past several decades. (Reingold, 2014)

While much of the existing research examines analysts’ responses to firms with new or unique strategies, there exists little research on how analysts adapt to new industry categorizations. As new industries emerge because of technological change, both experienced and novice analysts start following these new industries. The question thus arises: as new firms populate the nascent industry category, do analysts change their evaluative schemas to reflect the technological change or do they exert pressure on firms in the new industry category to adhere to prior-developed evaluative schemas? As new industries such as artificial intelligence, autonomous vehicles, and fintech emerge in response to technological innovation, it is imperative to understand how analysts adapt to these changes.

Analyst Evaluative Schemas

In asking “What type of firm is this?,” analysts apply existing evaluative schemas to firms to evaluate and assess the firm according to prior set expectations. When firms change their technological strategies or adopt unique strategies, research shows that analysts are slow to update their evaluative schemas to incorporate these changes. Rather, analysts generally stick to previously developed schemas of evaluation, resulting in their discounting of firms with unique or novel strategies. Tripsas (2009) showed, for example, that analysts who initially classified “Linco” as a photography firm when it went public continued to classify the company as a photography firm, even after Linco reoriented its strategy to market itself as a digital memory firm. Tripsas (2009) also showed that these classifications mattered in market projections, financial models that analysts applied to Linco, and their future growth projections of the firm. Similarly, when firms implement radical technological innovations in their strategy, analysts remain more positive and attentive to firms that keep with the existing technologies (Benner, 2010). Feldman (2016) found that firms that undertook “legacy spinoffs” (that is, spin off its original, or “legacy” business) enjoyed better stock market performances as compared to non-legacy spinoffs.

In another stream of research, McKendrick and Carroll (2001) found that the disk-array industry did not emerge as a legitimate industry category because it constituted mainly incumbent firms with operations in other industries and very few *de novo* firms. The authors speculate that the presence of new firms in the industry would have helped security analysts recognize the disk-array industry as a novel, legitimate industry category. These examples show, first, that analysts exhibit cognitive inertia in updating their evaluative schemas for incumbent firms they are already following (Tripsas, 2009; Feldman, 2016). Analysts are slow or reluctant to change the classifications and evaluative schemas that they apply to incumbent firms when the firms seek to enter a new industry category. Second, they suggest that analyst schemas are relevant not only for the classification of firms but also for the metrics that analysts apply to evaluate these firms.

While this body of work has looked at how analysts exhibit reluctance to update their evaluative schemas, it has not addressed the cognitive effects of analysts’ previous experience and expertise on their evaluations. In addition, this work also does not explore the variation in analysts’ evaluations of a focal firm but assumes that analysts are uniform in their evaluations. In exploring the effects of analysts’ previous experience and expertise and examining the variations among analysts’ assessments of the focal firms, we can start constructing answers to why some analysts adhere to their previously developed evaluative schemas. To address these gaps, my research examines how analysts' previous industry experience influences the structure and content of their evaluations. Specifically, my research examines the cognitive complexity of analyst evaluations in the context of a new technological category. In new categories, schemas of evaluation are not yet established, hence analysts are likely to devise evaluative criteria that best fit the firms in the new category. In their search for new evaluative criteria, analysts' cognitive styles are likely to influence how they process new information in the context of a new technology. Understanding the cognitive underpinnings of analyst interpretations of new technology is important because as Beunza and Garud (2007) show, analysts interpret new firms such as Amazon using a wide range of cognitive frames that influence the analyst's earnings estimates of the firm, classifications of the new firm, comparable competitors, and the key metrics used for evaluation. Cognitive styles thus influence the aspects of a new technology that analysts highlight in their evaluative criteria, which in turn shape audience understanding of the new technology.

In the context examined here, internet technology, analysts were undecided about the classification of firms in the nascent stages of the industry emergence. One analyst categorized 724 Solutions, a dot-com firm, as belonging to the financial services industry:

> Our initial research into valuation of 724 Solutions brought us to the realization that this is a very early-stage company that is developing products and services to support new, but potentially huge, industry. With that being said, 724 Solutions has successfully secured many of the world's top financial institutions as both equity partners and customers in a short period of time. We believe that any potential competitors will face significant barriers to entry in the financial services industry because of 724 Solutions's

> customer relationships that represent a potential end user base of more than 270 million individuals.

Another analyst following 724 Solutions classified it as a software firm:

> Residing on the higher value-added portion of the software value chain, comparable valuations would suggest Aether, InfoSpace, and Phone.com (all of whom are software/service providers in the wireless space), to be most reflective of 724 Solutions valuations relative to their market opportunity.

These examples show that analysts' interpretations of 724 Solutions not only influenced the firm's comparable peers, but also its future prospects.

Analysts also debated about the appropriate valuation tools to estimate the price targets of the dot-com firms. An experienced analyst following the internet firm ICG mentioned in his report that the appropriate way to value firms is price-to-earnings and cash flows, and this valuation technique cannot be applied to valuing ICG:

> Internet holding companies are not valued on traditional valuation measures (price-to-earnings and price-to-book). The ideal way to value a holding company is to analyze cash flow (that is, the cash flow of the partner companies). We believe that over the long term (5 to 10 years), ICG will be valued on cash flow. Unfortunately, given the early-stage nature of ICG's partner companies, we cannot value the long-term cash flow potential of ICG. Thus, we cannot produce a discounted cash flow analysis yet. Complicating the valuation of ICG is that the company currently only has six companies public at a value of $4.0 billion, and putting a price tag on the private companies is virtually impossible.

Another novice analyst following ICG tried to value the firm using a "sum of parts" valuation—that is, valuating different operations of ICG through different valuation techniques:

> The ability of ICG to successfully bring its companies public is controlled by the market's appetite for new B2B offerings. Additionally, the private equity piece of our valuation is the largest part of ICG's Net Asset Value, representing the majority of ICG's partner companies, for which we do not have a great deal of visibility. As such, this piece is also the most speculative. A great deal of the valuation will depend on whether or not ICG can continue to achieve 400% returns on their investments. We arrive at our $48 price target through a sum of the parts analysis.

The above quotes from analyst reports on internet companies also illustrate analysts' discourse regarding the classification of the focal firm, selection of evaluative criteria, and valuation tools used. Paying attention to the elements of analyst discourse is important to our understanding of how evaluative schemas are chosen to assess firms in nascent industry categories.

Hsu (2006) argues that a "fundamental goal of a critic is to construct and promote schemas of evaluation that are regarded as justifiable by others in the market." Especially in a new market context when evaluative schemas are emerging, analysts try to establish themselves as experts on the new technology through their evaluative schemas that can help investors differentiate, compare, and rank the firms in the new industry category. As evidenced in the dot-com era, analysts like Henry Blodget and Mary Meeker became internet industry experts based on their distinctive evaluative schemas on internet firms.

To capture the comprehensiveness of analyst evaluations, I introduce a construct called *evaluative complexity* which I define as the extent to which an analyst incorporates differentiation, uncertainty, and specificity in his or her justifications. I discuss the construct and its theoretical foundations in the next chapter.

Chapter 3 Theory and Hypotheses

Cognitive complexity is a psychological construct that indicates the "the degree to which individuals and teams construe their social world in a multidimensional way" (Wong, Ormiston, and Haselhuhn, 2011: 1479). Although prior studies on managerial cognition have used various definitions of cognitive complexity, a common central characteristic is the degree of differentiation between distinct constructs represented in arguments (e.g., Hale, 1980; Hitt and Tyler, 1991). Cognitively complex individuals have the ability to distinguish between alternative viewpoints and consider multiple perspectives in arriving at a solution or point of view. A differentiated viewpoint also acknowledges the ambiguity and multidimensionality of situations.

It is important to note that cognitive complexity can have both positive and negative effects on decision-making depending on the information contexts (Downey and Slocum, 1982; Finkelstein et al., 2009). Finkelstein et al. (2009) suggested that higher cognitive complexity can lead to "decision paralysis" and ambiguous messages. On the other hand, management scholars found that cognitive complexity positively influenced executives' decision-making (e.g., Wong et al., 2011; Maak et al., 2016). In one such study, McNamara et al. (2002) find that complexity of top managers had a positive effect on the number of strategic options they consider and on firm performance. Nadkarni and Narayanan (2007) found that the complexity of CEOs' cognitive schemas increased strategic flexibility and promoted success of firms in fast paced industries. Thus, cognitive complexity can have important positive or negative implications for managerial decision-making contingent on the decision-making problem and the informational context.

Considering these discussions, cognitive complexity is an important factor for understanding analyst evaluations in new industry categories. In uncertain informational contexts, such as new industry categories, actors ranking high on cognitive complexity look for novel information (Streufert and Swezey, 1986) involving a broader search and are willing to apply multiple competing and complementary interpretations (Bartunek, Gordon and Weathersby, 1983). Psychological research suggests that actors with low cognitive complexity see problems as “black or white” and possess a general unwillingness or inability to accommodate and acknowledge uncertainty and divergent viewpoints (Graf-Vlachy, Bundy and Hambrick, 2020). Conversely, actors with high cognitive complexity have a greater ability to acknowledge alternative perspectives and concepts and have higher acceptance of uncertainty (Thoemmes and Conway, 2007).

Studying analyst evaluations through the lens of cognitive complexity can yield important insights into how analysts structure and compose their evaluations. Specifically, examining the complexity of evaluations helps us understand whether analysts consider multiple viewpoints in their firm assessments, are receptive to including diverse information by paying attention to firm-specific strengths in their evaluations, and are overly optimistic or pessimistic of the nascent industry firms. In short, applying the construct of cognitive complexity to analysts’ evaluations helps us discern their comprehensiveness. While earlier conceptions of complexity focused on an actor’s ability to differentiate between constructs, later applications of the construct expanded it to include nuance as another key element of complexity. Nuance indicates that actors are not only able to differentiate between viewpoints but are also able to organize and compare them in meaningful ways (Wong, Ormiston, Haselhuhn, 2011). Scholars have suggested that apart from the ability to see different viewpoints, cognitively complex individuals are also able to see gradations in constructs (Wong, Ormiston, Haselhuhn, 2011). Hale (1980) suggested that cognitive complexity is moving "from a state of relative globality and lack of differentiation to a state of increasing differentiation, articulation, and hierarchic integration."

In line with these conceptualizations of cognitive complexity, I define analyst evaluative complexity as the extent to which an analyst incorporates differentiation, specificity, and uncertainty in his or her justifications—three components of evaluative complexity that capture differentiation and nuance.

Anecdotal evidence from prior research suggests that the ability to arrive at complex evaluations through consideration of multiple scenarios or viewpoints in their calculations is central to analysts' capability (Buenza and Garud, 2007). Especially in the context of nascent markets, where there is higher uncertainty and ambiguity compared to established markets, incorporating alternative perspectives in arriving at firm recommendations is key to a comprehensive analysis. New markets have less developed understandings of the products and processes (Navis and Glynn, 2010) and are characterized by industry structures that are still forming, so the nature of competition, supply chains, and other aspects of the environment are uncertain. This lack of common understanding of market characteristics and the lack of information on the new firms merit a comprehensive, multi-dimensional perspective by analysts following these entrepreneurial firms. Below I discuss the three components of evaluative complexity in detail:

Differentiation in Analyst Justifications

A differentiated perspective is one that takes into account multiple viewpoints and a range of possible scenarios. Differentiation is a fundamental characteristic of cognitive complexity—cognitively complex actors consider multiple perspectives in their decision-making and are able to differentiate between alternative viewpoints (Bieri, 1955). This is an important attribute of analyst information processing and reporting because it enables analysts to arrive at firm valuations after a comprehensive analysis. Buenza and Garud (2007) noted that final price targets are only an output of a process where the analysts decide between different scenarios or weigh their likelihood appropriately in rendering judgments. Inclusion of diverse perspectives also helps investors make better informed investment decisions. Prior research has highlighted that investors rely less on the stock recommendations of analysts than on the diverse perspectives an evaluation can provide (Groysberg and Healy, 2013). A New York based portfolio manager stated that, "Nobody relies on a buy or a hold. What you want is to listen to an articulate case from both the bull and bear views" (Brenner, 1991: 25).

Specificity in Analyst Justifications

In addition to differentiation, cognitive complexity also includes the ability to incorporate nuance into decision making. Wong et al. (2011) note that cognitive complex actors "tend to see gradations in constructs and interrelationships among them." Nuanced thinking enables cognitively complex actors to derive comparisons and contrasts between the diverse viewpoints (Graf-Vlachy, Bundy, and Hambrick, 2020). In line with the conception of gradation as an indicator of cognitive complexity, I also consider the specificity of justifications in analyst reporting. Specificity is an indicator of the analysts' focus on firm-based factors or market-based factors in their evaluations.

According to strategy scholars, the two main categories of determinants of firm value are a firm's resources or capabilities and industry characteristics (Barney, 1986; McGahan and Porter, 2002). The differences between the firm-based and market-based sources of value can also be related to the classical debate in strategy regarding the sources of performance differences among firms (McGahan and Porter, 1997). While the resource-based view holds that performance differences originate from the differences in a firm's resources and capabilities, the structure-conduct-performance paradigm posits that industry structure is a central determinant of firm performance.

Analysts write two kinds of reports—industry reports that focus on industry trends and firm reports that discuss how a focal firm's strategic decisions such as product introductions, acquisitions, or market expansions impact their financial performance. In their assessments, analysts can focus on firm-specific attributes as contributors to a firm's value or they can focus on the broader, decontextualized market features.

On a continuum of firm to market, analysts vary in identifying the sources of firm value: on the one end are firm-specific factors, on the other end are market-specific factors, or they could consider a mix of both. I define firm-based justifications as justifications that focus on firm attributes. The underlying logic behind firm-based justifications for valuation is that every firm is unique in its resources, product offerings, capabilities, or strategies and that every firm has an intrinsic value that can be estimated, based on the firm's tangible and intangible assets. These justifications thus point to the heterogeneity of firms within a market based on the unique features of specific firms and thus provide a comparative basis for firm evaluation in any given market. Navis and Glynn (2010) argue that firms try to differentiate themselves from other category members by emphasizing their distinctiveness from their peers in the same industry.

Differentiating helps firms establish their uniqueness in the minds of their external audiences and thus helps them in the acquisition of key resources. Firm-based justifications require consideration of market characteristics and firm resources, as they address how firms are positioned in the market space.

I define market-based justifications as justifications that focus on market attributes. The implicit rationale behind market-based justifications is that the value of a firm is determined primarily by its membership in a market category. Market-based justifications assume that there is a tight coupling between industry characteristics and firm performance. Market attributes like novel technology, estimated growth, and stage of industry life cycle are seen as sources of firm performance and profits, which are dependent on the industry life cycle. For instance, negative earnings and negative cashflows of firms are seen as a consequence of initial stages of industry life cycle, rather than as a failure of the firm's strategy. Moreover, these justifications often implicitly assume that other firms in the same market perform similar to the focal firm. Market-based justifications can be related to the structure-conduct-performance paradigm that states that industry structure and characteristics influence performance of firms within an industry (Bain, 1956). The key assumption of market-based justifications is homogeneity of markets. Market attributes provide key guidance to focal firm performance and evaluations. In the context of the internet industry, these justifications took the form of exponential growth of internet-related markets, revolutionary connectivity to a wider customer base, and the role of internet technology in transforming availability of information. These justifications imply that a market's novel attributes and future growth potential can be a basis for firm valuations. This way of linking the focal firm to other firms in the market lends legitimacy to organizations that are part of the same category (Elsbach and Kramer, 1996). Market-based justifications also tend to attribute fluctuations in firm performance to market-related factors by highlighting collective risk factors in the larger market context.

In assessing the sources of firm value, focusing on specific and relevant firm attributes requires more attention to and understanding of unique firm capabilities and strategies on the part of the analyst. Firm-based justifications assess a firm's position within the industry environment, while market-based justifications mainly assess the broader industry structure. Focusing on firm attributes also suggests that an analyst is able to comprehend distinctive firm strengths and offer a comparative or graded sense of the firm in relation to its competitors (Navis and Glynn, 2010). Firm-based justifications are more complex because they involve description of specific firm attributes and how they advantage or disadvantage the firm in seizing opportunities and avoiding threats in the environment. While general market attributes like growth of the internet, connectivity to a wider customer base, and the role of internet technology in transforming availability of information can be considered as input to firm valuations, in and of themselves they require less specificity or nuanced understanding on the part of the analyst. (Appendix 1 lists some examples of analyst justifications in arriving at target price estimates, extracted from analyst reports.)

Uncertainty in Analyst Justifications

In addition to including multiple viewpoints and practicing nuance in evaluating these viewpoints, another important indicator of analysts' cognitive complexity is how they process and convey the ambiguity of informational cues. Prior research has indicated that low complexity actors view issues in black-and-white terms (Wong, Ormiston, Haselhuhn, 2011) and fail to take into account that outcomes or scenarios have likelihoods of occurrence linked to them. Given that nascent markets are often uncertain in terms of future outlook and growth potential, analysts' ability to express uncertainty in such nebulous contexts can be a key indicator of the complexity of their communication.

Schematic Information Processing in Uncertain Contexts

Actors are boundedly rational in their information processing capabilities (Simon, 1955)—that is, they are bounded in their capacity to pay attention, consider all possibilities, and process all available information. In order to maximize efficiency in information processing, therefore, actors develop cognitive mechanisms, such as schemas. Schemas, or mental templates, are knowledge structures that contain categories of information and the relationships among them (Bingham and Kahl, 2013) and help actors process information in a faster and more efficient way (Walsh, 1995). As abstract representations of accumulated knowledge, these top-down knowledge structures help actors process complex and ambiguous information and facilitate decision making.

A schema can be defined as a "mental template that individuals impose on the information environment to give it form and meaning" (Walsh, 1995: 281), and it is a fundamental concept that has been studied in multiple literatures, including social cognition, institutional theory, and behavioral theory of the firm. While research in each of these areas has examined the concept of schemas and their influence on individual decision making, there are some key differences in their conceptualization of schema formation and enactment (DiMaggio, 1997; Walsh, 1995).

Research on social cognition indicates that past experiences guide actors' information processing through mental models or templates, i.e., cognitive schemas, that help organize information (Fiske and Taylor, 1991; Walsh, 1995). The knowledge structures from past experiences thus guide how individuals interpret and encode new information and accelerate complex information processing in ambiguous new environments (Walsh, 1995). Psychological studies have shown that individuals with prior experience in a domain have cognitive schemas for that domain and those without prior experience do not (Lurigio and Carroll, 1985). While cognitive schemas can be helpful in processing information, the application of schemas based on past experiences can also lead to a selective perception of information and to biases in information processing (Dearborn and Simon, 1958).

Research in institutional theory takes a very different approach and views schemas as guided by institutional norms and defined at the level of social interactions. In this interpretation, institutions are enacted through schemas or scripts, which are seen as "behavioral regularities instead of mental models" (Barley and Tolbert, 1997). According to Barley and Tolbert (1997), scripts are "observable, recurrent activities and patterns of interaction characteristic of a particular setting." Similarly, researchers studying institutional logics view schemas as enactments of a particular logic or "logics in action" (DiMaggio, 1997) that guide action and decision making (Thornton, Ocasio and Lounsbury, 2012). Schemas thus relate to the cognitive dimension of institutions that govern behavior in a given situation (Misangyi, Weaver and Elms, 2008). According to this view, "institutional persistence and conformity arise from automatic enactment of scripts and habits" (Misangyi, Weaver and Elms, 2008: 755). Actors initiate institutional change by intentionally invoking schemas related to an alternative institutional logic (Seo and Creed, 2002). Research in this tradition often views actors as automatically invoking schemas and scripts in a given institutional context and, further, assumes that schemas are uniform across actors in a particular institutional context.

Behavioral theory of the firm, rooted in the neo-Carnegie perspective (March and Simon, 1958; Cyert and March, 1963), is a foundational theory that examines decision making within organizations. According to this perspective, actors are boundedly rational—that is, they are limited in their cognitive capabilities and have limited time to make decisions. Due to these limitations, actors form imperfect cognitive representations regarding their environment (Gavetti and Levinthal, 2000), and yet these representations are key determinants of their problem space (Simon, 1973) and their actions (Tversky and Kahneman, 1981). According to this view, actors develop cognitive schemas over time with experience to increase their attention towards relevant stimuli and enhance their responses in stable environmental settings (Ocasio, 2011). Thus, actors interpret environmental cues depending on the action-outcome linkages they form based on their prior experience. In this sense, experiential learning leads to actors' sensemaking of their environment (Gavetti and Levinthal, 2000). Like the socio-cognitive perspective, behavioral theory of the firm also predicts that prior cognitive orientations result in selective attention to problems (Ocasio, 2011).

Cognitive schemas formed through experience are related to local search (based on experience), as opposed to distant search (based on exploration). Actors engage in local search for problem solving that is based on "exploiting" pre-existing knowledge or experiential knowledge (Katila and Ahuja, 2002). This type of search might make actors resistant to change and hinder their adaptation to new environments. On the other hand, distant search entails exploration of new knowledge and moving away from pre-existing routines and mental representations (March, 1991). Actors engage in distant search when the problem falls outside their current knowledge or skill set. Exploration helps actors adapt to environmental changes (Levinthal, 1997; Eggers and Kaplan, 2009).

Competency Traps and Experience

Research on organizational learning posits that as organizations gain experience in a particular domain, they develop competency traps (Levitt and March, 1988) that inhibit them from adopting to changing environments. Competency traps arise because of a positive feedback loop between competence and experience—as organizations gain more experience in one domain, they tend to engage in activities where they have competence and avoid activities where they have less competence. In turn, as organizations engage in these activities, they gain even more experience in those organizational areas. The self-reinforcing cycle of experience and competence is accentuated in times of uncertainty (Ahuja and Lampert, 2001).

Organizations that have developed efficient routines of functioning find it difficult to change their operational procedures because it is less rewarding to gain through a new domain, given the sunk costs in the existing domain. Management research in this area has shown that as organizational age increases, organizations pursue competencies based on previously developed competencies. Often, these competencies tend to expand on existing routines while lagging behind on cutting-edge areas. Extensive organizational knowledge in a particular domain leads to cognitive inertia and makes it difficult for older organizations to adopt to changing external environments.

Critics such as security analysts develop expertise in a particular industry by investing time and effort to learn about industry knowledge and build connections to firm management in that industry. Analysts also "construct and promote" evaluative schemas suitable to a particular industry that are valued by other analysts and investors and help the analyst stand out from peers (Hsu, 2006). In this way, analysts are rewarded for their distinctive analysis and viewpoints on a given industry. Building on this research on competency traps in organizational learning, we could expect that analysts with experience working in a previous industry are likely to fall into competency traps regarding their evaluative schemas when they start following a new industry category.

Experience and Cognition

The behavioral theory of the firm posits that actors' cognitive schemas or knowledge structures influence their decision-making (Gavetti, Levinthal and Ocasio, 2007). When actors engage in schema-based processing, they make assumptions, plan alternatives, and evaluate consequences regarding the environment depending on their cognitive schemas (March and Simon, 1958; Walsh, 1995). Research on managerial cognition suggests that schemas are formed on the basis of actors' prior experiences and thus an individual actor's tenure in a role influences the content of the knowledge structures they develop (Walker 1985; Wagner, 1987). As actors gain expertise in a specific domain, their domain-related cognitive schemas become better structured (Newell and Simon, 1972).

Structured schemas enable experienced actors to engage in faster and better decision-making in the contexts to which they are suited because practice and the routine application of structured schemas means they are processing information in a stable and reliable fashion. By drawing on previously learned and abstracted knowledge, they increase their problem-solving efficiency (Lurigio and Carroll, 1985; Fiske and Taylor, 1991). More specifically, individuals who have prior experience in a domain have schemas that can be more readily and reliably accessed than those of individuals without prior experience (Walsh, 1995). Thus, experts' problem-solving efficiency stems from their activation of previously developed schemas based on informational cues in the current context (Gick, 1986) and “top-down” information processing where existing knowledge structures guide identification of solutions (Walsh, 1995). With schema-driven information processing, experienced actors develop simple, heuristic rules (Aarts, Verplanken, and van Knippenberg, 1998) and reject alternatives early in their decision process. They can therefore bypass the process of searching for alternative solutions and directly invoke previously recognized solutions (Gick, 1986).

On the other hand, novices engage in “bottom-up” problem-solving approaches that use information in the current context to guide sensemaking of the environment (Gick, 1986; Walsh, 1995). In the absence of previously developed cognitive schema, novices are likely to gather information and consider alternative search strategies for problem-solving. The bottom-up approach to information processing involves the development of fluid and evolving codes and categories for issues and stimuli (Weick and Sutcliffe, 2006). Psychological research on problem-solving by novices indicates that inexperienced actors engage in a more cognitively demanding decision-making process (Aarts, Verplanken, and van Knippenberg, 1998), pay more attention to a wider set of environmental features, and are flexible in their attention to external stimuli in decision-making situations due to a lack of prior knowledge structures (Marchant et al., 1991; Sternberg and Frensch, 1992; Rosman, Lubatkin and O’Neill, 1994).

While experienced actors can increase their problem-solving efficiency by engaging in schema-based or “top-down” information processing, there are potential downsides to it. Research on cognition suggests that experience leads to functional fixedness (Duncker, 1945), meaning an actor has a fixed way of thinking about a problem. Experts in a specific domain are less likely to adapt to changing conditions or new rules within their domains of expertise (Sternberg and Frensch, 1992). As experienced actors rely on schema-based processing that reinforces existing routines and hinders adaptation, their schemas can become resistant to change (Gersick and Hackman, 1990). Such routinization often results in an automatic or reflexive application of schemas (Aarts and Dijksterhuis, 2000). Research has also shown that in new contexts with high uncertainty, new information, or rules that are different from previous contexts, experienced actors are more likely to engage in automatic schema-based processing, applying previously developed cognitive schemas in a reflexive manner (Nystrom and Starbuck, 1984; Birch and Bloom, 2007). In such contexts, experienced actors are less likely to notice information that is inconsistent with their existing cognitive schemas (Von Hippel et al., 1993), as schemas influence the information that actors retain and recollect from new contexts. As Bartlett (1932) showed, subjects remember and interpret information in ways that are consistent with their existing schemas but inconsistent with the actual data. Moreover, experienced actors are more likely to use cognitive shortcuts or "rules-of-thumb" that are developed through prior experience to guide their decision-making in new contexts (Bingham and Eisenhardt, 2011). Thus, schema-based processing by experienced actors in new contexts might result in an inaccurate representation and interpretation of information, and the simplistic application of previously developed cognitive schemas.

Analyst Prior Experience

The above theoretical arguments suggest that analysts who have prior experience evaluating and analyzing firms in other industries are likely to develop cognitive schemas for identifying and processing information for firm evaluations. Security analysts' domain-specific schemas might include industry-specific knowledge and cognitive "rules-of-thumb" for firm evaluation in a specific industry. When experienced analysts start following firms in a new industry, it can be expected that their prior industry experience and expertise will shape their evaluation of firms in the new industry. In ambiguous new market contexts, with complex and confusing informational cues, experienced analysts are especially likely to rely on schema-driven information processing to identify relevant information for firm evaluations. In doing so, experienced analysts might not update their schemas based on relevant information in the new contexts or they might screen out vagaries in information that do not fit their existing cognitive schemas. I argue that experienced analysts are likely to reflexively invoke previously developed cognitive schemas resulting in a simplification of information used to evaluate firms in new markets. Such a reflexive and simplistic application of schemas might lead to less cognitive complexity in their justifications.

On the other hand, inexperienced analysts, who have relatively little experience evaluating firms, will have less structured cognitive schemas for evaluation. In the absence of prior schemas, inexperienced analysts are more likely to engage in bottom-up information processing based on context-based informational cues. Bottom-up information processing is cognitively more demanding as actors need to consider more information in their search criteria. Given their lack of prior knowledge structures, inexperienced analysts are also more likely to be flexible in their search process, paying attention to a wider set of evaluative criteria in their analysis and in responding to external stimuli in their decision making. Thus, I argue that inexperienced analysts are more likely to pay closer attention to firm-specific informational cues leading to more complexity in their justifications.

Hypothesis 1 (H1): Analyst evaluative complexity of justifications will be lower for experienced analysts as compared to inexperienced analysts

Analyst Prior Status

Status refers to the relative position of actors in a social system (Parsons, 1951) that bestows various advantages, like public appreciation and deference, to actors who occupy high-status positions (Weber, 1968). While status can yield positive external rewards, it can also lead to "competency traps" (Levinthal and March, 1993) by providing a positive feedback loop between an actors' skills and knowledge and the expected rewards. Levinthal and March (1993) suggest that such self-reinforcing mechanisms result in actors becoming focused on certain skills while neglecting others, resulting in myopia of learning. Research on the reinforcement-expectancy model of learning suggests that actors tend to repeat actions that were previously rewarded (Cyert and March, 1963). Building on this literature, I argue that actors who are conferred with high status are more likely to exploit the capabilities that are perceived or assumed to have led to high status, which in turn can lead to competency traps that impede adaptation. Prior success also leads actors to lock into rigid cognitive schemas (Prahalad and Bettis, 1986) and reduces information seeking and adaptation to new contexts (Miller and Chen, 1994).

Prospect theory (Kahneman and Tversky, 1984) posits that individual actors are averse to losses and that a "loss from a reference position is perceived to be more distressing than are the benefits from a corresponding gain" (Bothner, Kang and Stuart, 2007: 214). In line with this argument, high-status actors are likely to be averse to losing their status, than gaining additional benefits from status rankings and are likely to be protective of their current status positioning. Thus, high-status actors have a greater incentive to maintain status-quo than low-status actors and take actions that ensure that their status ranking persists, especially in contexts where such stability is not guaranteed (Jordan, Sivanathan and Galinsly, 2011; Bowers et al., 2014).

Consequently, high-status actors are more likely to rely on prior schemas—and schema-based processing—to repeat actions that gained them status conferral in the past. As we have seen, reliance on schema-based processing is likely to lead to simplistic ways of information processing in new information contexts. Thus, I argue that status gain might result in the in the reduction of an actor's relative cognitive complexity when evaluating new and uncertain environments.

In the case of security analysts, high-status is attained when an analyst gains "all-star" ranking in *Institutional Investor* magazine. Since 1972, *Institutional Investor* has ranked the top four (first, second, and third place, and runner-up) "star" analysts by industry, selected through an investor poll each year. These analysts are listed in the "All-America Research Team" rankings by industry, and they enjoy increased remuneration, visibility and recognition as compared to their counterparts (Groysberg, Lee and Nanda, 2008). These rankings serve as a proxy for analyst quality and star analysts are typically considered as experts in their respective industries (Groysberg, 2010).

In established markets, investors know which analysts are more accurate and credible, due to availability of historical data on past analyst estimates. A buy-side analyst said:

> I started my career being a consumer analyst, that was over 15 years. So, I've got a very good understanding over the years that I've developed. I know who's good [on the sell-side], who's not good. And I know which ones to look at, which ones I won't look at. So, what you end up doing as a buy-side, and it just comes by experience is that you develop a shortlist of analysts that you want to look at. When I look at the analysts, there's maybe 35 or so covering the stock, I really care about 3 or 4. That is based off my experience of

following these analysts over time, I'm seeing how accurate they are and the access they have to management.

On the other hand, new market contexts provide opportunities for low-status analysts to gain status rankings and the rewards associated with high status. First, in new markets analyst credibility is not yet established, expertise on the new industry category is undecided, and this provides an incentive for low-status analysts to aim for higher status. Second, investors value different informational inputs from sell-side in established and nascent markets. In established markets, factors such as access to management, information on earnings revisions are useful to investors, whereas in new markets, information on the emerging technology, industry business models, growth prospects are valuable to investors. Given that institutional investor rankings are based on investor polls, experimenting with novel evaluative criteria benefits low-status analysts, more than high-status analysts in new markets as low-status analysts have a potential upside of All-star rankings and no significant perceived downsides in new markets.

For these reasons, I argue that security analysts who were conferred high-status are more likely to rely on prior schemas and less likely to change such schemas in a new market context. Industry knowledge is a primary criterion on which investors vote for the best analysts (Buenza and Garud, 2007), and thus high-status analysts are more likely to display entrenchment of schemas due to past rewards of such knowledge, leading to cognitive inertia in adapting their justifications to new industries. I argue that because all-star analysts are specifically rewarded for their past performance, they are more likely to use schemas and evaluation metrics that previously gained them social appreciation. These high-status actors will also be more likely to invoke prior-cognitive schemas in new industry contexts, ignoring contextual information that is inconsistent with such schemas, leading to a simplistic application of these schemas to such contexts. Conversely, low-status analysts, envisage potential gains from flexible evaluative criteria that are context-driven, resulting in detailed and complex evaluative schemas.

Hypothesis 2 (H2): Analyst evaluative complexity of justifications will be lower for high-status analysts as compared to low-status analyst

Chapter 4 Research Design and Methods

Research Context – Internet Industry

The internet industry's origins can be traced back to the mid-1990s with the introduction of the world-wide-web in 1993. Beginning in 1994, a host of internet startups or dot-com firms emerged whose business proposition was that they conducted most of their business transactions online, typically through a website. The main feature of the dot-com startups was that their operations were primarily internet-based, with products and services delivered through internet-based means. Many of the dot-com startups also offered software solutions and services, rather than a physical product or offering.

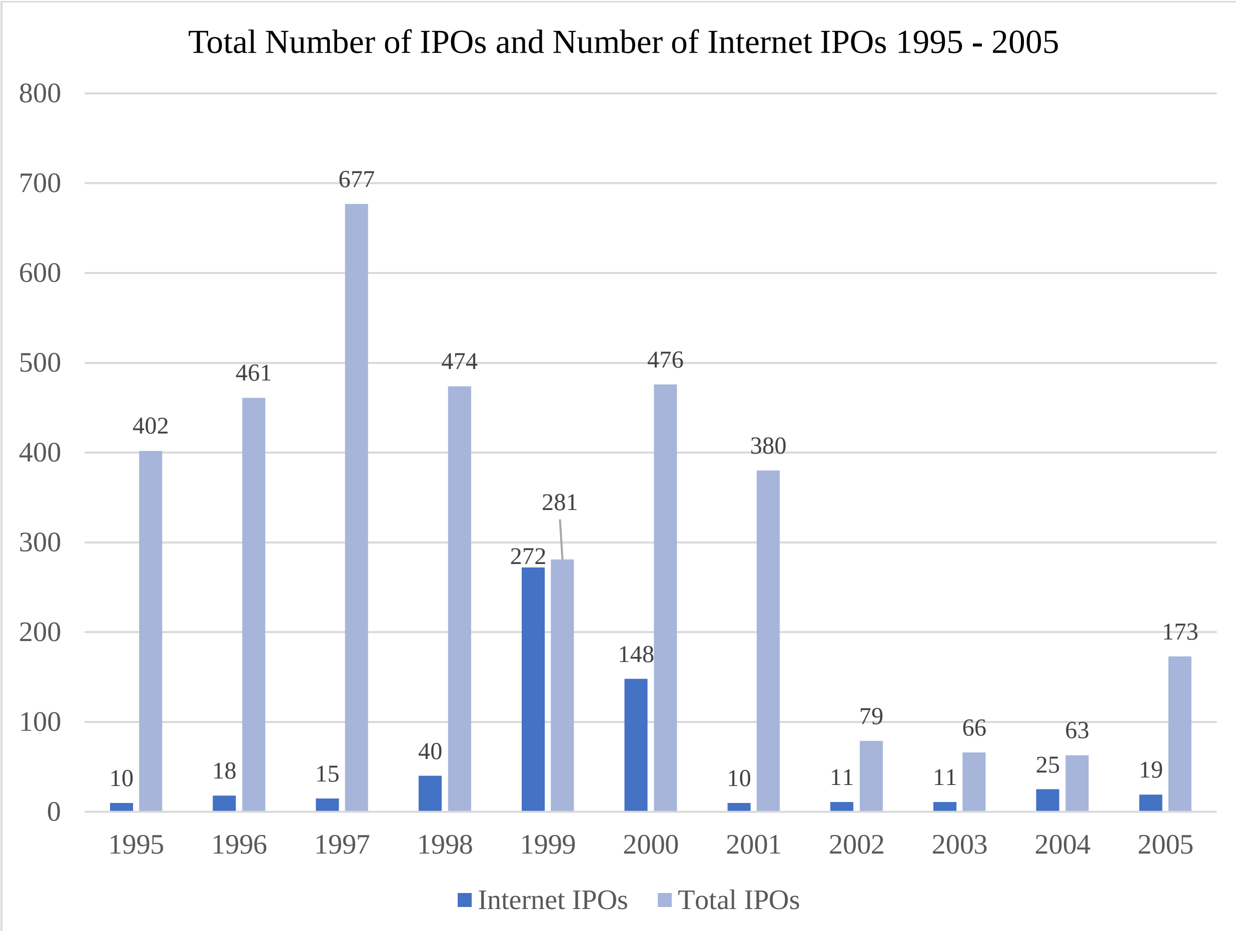
With the rise in the number of internet-based startups, the internet industry was hailed as a harbinger of the "new economy"—a term used for high-growth industries driving economic growth, and a term typically used for industries that are based on advanced technologies. Firms based on these novel technologies were significantly different from established industries. The advent of the internet was compared to the introduction of revolutionary technologies—like the telegraph,[1] electricity, the automobile, and the airplane[2]—in terms of the effect these new technologies had on increasing productivity, reducing communication barriers, and transforming the economy. In the mid-1990s, many industry experts predicted that the internet would

[1] https://www.csmonitor.com/2000/0621/p3s1.htmla
[2] https://news.microsoft.com/2000/12/01/shaping-the-internet-age/

transform production systems by reducing geographical and logistical barriers and the cost of communication and by increasing flexibility of operations (Goldfarb and Kirsch, 2019). For instance, internet firms could have more subscribers than national magazines or newspapers. For these reasons, as a high-growth industry, many internet start-ups began issuing initial public offerings on the stock market. Starting with NETCOM Online Communications in December 1994, the number of internet firms that registered for an initial public offering on the US equity markets rose to 650 by the year 2005.

However, the advent of the internet industry also brought a high degree of uncertainty regarding the financial valuations of internet firms. Many of the internet start-ups did not have steady revenue streams, positive profits, or assets, and could be easily imitated. Most of the internet firms also focused on "growing big fast" (Goldfarb and Kirsch, 2019)—that is, capturing as many customers as possible at high customer-acquisition costs or making business losses. Internet also gave more power to the customers, as customers could access information across competitors to make a purchase and hence could force firms to decrease their prices. With the popularity and high-growth of internet IPOs, many analysts, both experienced and novice, started following internet firms. The internet industry thus provides an ideal context to study how analysts' prior histories shape their understanding of a new breakthrough technology. Secondly, this context is interesting as the high number of internet IPOs resulted in a mix of experienced and inexperienced, high-status and low-status analysts following the industry from its nascent stage.

Figure 1



Sample, Data and Measurements

My sample consists of all organizations that went public in the internet sector of the U.S. Stock Market from 1995 to 2005. Internet firms are not comprised from a single industry in the traditional sense of industry codes and definitions (Johnston and Madura, 2002). Rather, it is a technology which provides an electronic means of business for firms to complete transactions that were traditionally completed through physical means. Internet firms can span multiple industries and can be listed under various Standard Industrial Classification (SIC) codes. Firms as diverse as booksellers, automobile retailers, and flower shops can be listed as internet firms because they complete part of their operations through the web. Literature does not offer a singular definition of internet industry, and there exists some arbitrariness as to what comprises an internet firm (Loughran and Ritter, 2004; Johnston and Madura, 2002).

As my research pertain to all the publicly listed internet firms in the US stock exchanges, standard SIC codes are not applicable to arrive at the sample of firms. To resolve this issue, I first consulted Loughran and Ritter’s (2004) list of internet firms, that identified 564 U.S. based organizations with initial public offerings (IPOs) between 1995 and 2005. Loughran and Ritter (2004) compiled this list using industry SIC codes of technologically related industries like computer hardware, communications equipment, communications services, software etc. As discussed above internet firms can belong to a varied set of SIC codes and need not specifically belong to the technological domain. For instance, the above list would have missed booksellers like Amazon that were not listed as a technological company. Hence, I augmented the above list of firms with 48 additional organizations, from the population of all internet IPOs listed on the U.S. stock exchanges between 1995 and 2005 that used internet-related keywords (i.e., internet, online, web, electronic commerce, e-commerce, and e-business) to describe their businesses on Bloomberg. After excluding firms with missing data, my final sample was 454 firms.

Analyst Initiating Reports

I downloaded analyst initiating reports for the firms in my sample from the ThomsonOne database. These are the first reports filed by security analysts when they start following a publicly listed firm. Analysts who follow a specific firm provide periodic (quarterly) estimates of the stock price and earnings of the firm. However, only the initiating reports typically have detailed discussions by the analyst regarding the firm's financial details, product offerings, and competitors. More importantly, the initiating reports have a "Valuation" section where the analyst discusses in detail how he or she arrived at the target price for the firm—listing the valuation methods used, justification for the method, and any assumptions made. It is important to note that analysts discuss and provide explanations of the valuations and target prices mainly in the initiating reports. These assumptions are carried over in the analyst's subsequent reports and earnings projections and are rarely changed or discussed in further reports over the course of the time the analyst follows the firm. Typically, many analysts follow any given publicly traded firm, and there are thus multiple initiating reports for a single internet firm. For my sample of internet firms, there are a total of 1775 initiating analyst reports.

As analyst reports do not follow a specific format, they vary widely in terms of the sections and the key words used. This makes automated text extraction of a specific section impossible, as that would require the beginning key words and the end keywords of the section or the page number of the text that has to be extracted. This is a known problem in both accounting and strategy research. For my analysis, therefore, I manually extracted text from the valuation section of each analyst initiating report for the 1775 reports between 1995 and 2005.

Measurement of Variables

Dependent Variable

Evaluative complexity: ***Evaluative complexity***: Prior studies have measured cognitive complexity through manual scoring of texts (e.g. Wong, Ormiston, Haselhuhn, 2011), but this is not a practical method when working with a large volume of texts. Recent studies in cognition have used automated coding and text analysis to capture underlying psychological constructs in texts (Tausczik and Pennebaker, 2010). Linguistic Inquiry and Word Count (LIWC) developed by Pennebaker et al. (2007) is a well-established automated coding scheme to capture underlying psychological constructs in text data. LIWC uses word counts to map the occurrence of specific words to cognitive constructs (e.g., causal attributes) and language categories (e.g., pronouns). This software categorizes words into approximately 90 categories based on words and word stem matches, controlling for the length of the text using a dictionary of 6400 words. Recent studies in organizational literature have used LIWC to capture cognitive dimensions in organizational communications. For example, Crilly, Hansen and Zollo (2016) studied the language of decoupling in organizational sustainability reports using LIWC and coding of qualitative interview data. Another well-developed dictionary is the Loughran and McDonald (2011) financial sentiment word list that was designed specifically for use in finance-related texts. Graf-Vlachy, Bundy and Hambrick (2020) used a word count based on LIWC word categories supplemented by the Loughran and McDonald (2011) financial word dictionary to capture cognitive complexity in CEO communications. I draw on these two dictionaries and add context specific keywords relating to analyst reports in constructing my measure of evaluative complexity.

My measure of evaluative complexity consists of three components: differentiation, uncertainty, and specificity (summarized in Table 1).

Table 1 Three Components of Evaluative Complexity – Definitions and Measurements

Component	Differentiation	Specificity	Uncertainty
Definition	Ability to differentiate between alternative perspectives	Nuanced understanding of firm-specific factors	Communication of ambivalence
Source Dictionary	LIWC word category of "exclusive" words	Dictionary of firm-specific and market-specific keywords	Loughran-McDonald sentiment word-lists relating to financial uncertainty
Measure	Number of differentiation words divided by total number of words in text	Relative emphasis on firm vs. market attributes	Number of uncertain words divided by total number of words in text
Example words	Whereas, however, except	Strategy, execution, pipeline, revenue	Contingent, possibly, speculate

a) Differentiation in analyst justifications

The component of differentiation captures an analyst's ability to differentiate between constructs and to perceive multiple perspectives in their justifications. For instance, the below analyst report perceives presence of multiple market segments and distinguishes between focal firm performance in relation to its competitors:

> We believe that Foundry and Extreme really sell into mutually exclusive segments of the carrier market, whereas Riverstone has proven itself to be a competitive solution in both of the segments.

While the example below mainly focuses on earnings and revenues, and does not consider other perspectives in arriving at the estimates:

> The company reported earnings of $0.08 compared to the consensus estimate of $0.06. Revenues were up 251% from 2Q99. Revenue growth was driven predominantly by billable headcount growth of 21% and by an increase in revenue per professional to $385,000 from $364,000 in 1Q00.

To capture this dimension, I used the LIWC word category of "exclusive" words which indicates that the actors are drawing distinctions between constructs (Graf-Vlachy, Bundy and Hambrick, 2020). Tausczik and Pennebaker (2010) argue that actors use "exclusive" words to make distinctions between "what is in a category and what is not in a category." The "exclusive" word category in LIWC includes such words as "but" "whereas," and "however" for a total of 81 words. My measure of differentiation in analyst justifications is the number of "exclusive" words used divided by total number of words in the justification. This measure has been used by Graf-Vlachy, Bundy and Hambrick (2020) in their measure of CEO cognitive complexity.

b) <u>Specificity in analyst justifications</u>

Specificity captures the gradation in analyst justifications. To evaluate firms, analysts might situate their justifications of value on a continuum of firm-based justifications of value and market-based justifications of value. To measure the relative use of firm-based or market-based justifications used by analysts, I constructed a measure called "relative emphasis on firm vs. market attributes" as described below:

Relative emphasis on firm vs. market attributes: This measure captures the context-specific complexity in analyst justifications. I developed a dictionary of keywords to capture analyst use of firm-based or market-based justifications. To do this, I initially conducted a content analysis of the "valuation" section from the analyst initiating reports. Content analysis has been used in prior research to study organizational processes (Krippendorff, 2004). Analysts discuss their justifications of the valuations and target price projections of the new publicly listed firms in the "valuation" section of the initiating reports. I carefully read through many initiating reports to gain an understanding of the topics that analysts typically discuss in this section of their reports. I focused on two widely acknowledged justifications typically used in analyst evaluations: firm- or market-based justifications. Analysts can place relative emphasis on firm-level factors, such as its resources and capabilities, or on factors external to the firm, such as industry growth and industry structure.

In the following example, the analyst provides detail about the focal firm's products and their price points, with respect to its competitors:

> Extreme Networks provides high performance networking products at competitive price points. Products based on its latest "Inferno" chipset, such as the BlackDiamond and Summit 7i, continue to do extremely well.

Whereas in the excerpt below, the analyst focuses on broad market trends in their analysis:

> Lycos is a premier company because it is the momentum leader on the Internet, it should continue to expand its market share.

Following prior research (Mohr, 1998; Weber, 2005; Park and Zhang 2020), I implemented a semiotic analysis methodology to measure the relative emphasis on firm and market attributes in analyst justifications. I followed multiple steps to carry out the content analysis of analyst texts. First, I prepared the categories of justifications that analysts might use in their reports based on prior literature in accounting and in strategy. I then used a structured inductive process outlined in Weber (2005) to identify keywords associated with either firm-based justifications or market-based justifications used by analysts. An advantage of this type of measurement is that context-specific ambiguities relating to the use of words in a particular research context can be avoided and a closer link to the theoretical constructs of interest can be maintained (Weber, Patel and Heinze, 2013). I first randomly selected 10 analyst reports varying across time, analysts, IPOs, and investment banks and developed categories of keywords. I read each of the analyst reports, identifying and recording words and phrases and grouping them into justifications or explanations of value of the focal firm. I repeated this process by adding another 10 randomly selected reports to refine, revise, and simplify the keywords representing the two types of justifications. I repeated this process for 10 iterations (100 reports). The codebook for the firm-specific and market-specific is outlined in Appendix 2. I counted the specific keywords in the dictionary developed as described above using computerized content analysis. Some keywords from this dictionary are strategy, execution, pipeline and revenue.

I then constructed a variable indicating the relative emphasis on firm- or market-attributes in analyst text. For firm-attributes, I counted the total number of instances of keywords indicating firm-related words and the total number of instances of market-related keywords. To capture the relative emphasis of the analyst on firm- or market-attributes, I used the following formula to arrive at a score of relative emphasis on firm or market-attributes:

Relative emphasis on firm-attributes =

$$\frac{\text{count of firm−related keywords}}{\text{count of firm−related keywords} + \text{count of market−related keywords}}$$

c) Uncertainty

As a second component of evaluative complexity, I measured uncertainty expressed in analyst justifications. Prior research indicates that actors with low cognitive complexity perceive issues as black-or-white. Expressions of uncertainty indicate nuanced thinking, openness to new information, and multiple viewpoints (Conway III et al., 2012). It is more complex to express ambivalence than it is to express certainty. To measure uncertainty in analyst texts, I used the Loughran-McDonald sentiment word-lists relating to “uncertainty” (Loughran and McDonald, 2011), developed to analyze uncertainty expressed in financial documents. This dictionary consists of keywords such as ‘contingent’, ‘possibly’ and ‘speculate’.

The following example depicts that the analyst expresses uncertainty and potential risks in their estimates of the focal firm:

> While there is significant risk that Priceline may not achieve such stellar results, we believe the growth and profitability targets are achievable.

While the following analysis expresses surety about the firm prospects:

> Virage will be successful in its plans to reach profitability by FY:03 with rapid earnings expansion coming in following years.

Finally, I standardized and averaged the three components of evaluative complexity—differentiation, uncertainty, and specificity—to compute analyst *evaluative complexity* score for each year t.

Independent Variables

Analyst prior experience*:* I measured analyst experience as the number of years for which an analyst supplied at least one forecast estimate before following an internet firm. To obtain a list of analysts who followed internet firms in the period 1995-2005, I extracted the names of security analysts from the initiating reports downloaded from ThomsonOne. From this list, I shortlisted reports that are generated within 1 year and the 1^{st} quarter of the subsequent year of the firm IPO, as I am interested in the prevailing explanations of firm value at the time of IPO. From this shortlisted set of initiating reports with analyst names, I deleted all the reports with multiple analyst names as I am interested in individual analyst explanations of firm value. From this list of single authored analyst initiating reports, I removed duplicates, which left me with a list of ~563 unique names of analysts who had initiated the reports.

I then matched these analyst names to the names in I/B/E/S translation file to get the analyst codes for the analysts following internet firms. Matching and extracting analyst codes in the IBES database helps in identification of historical analyst earnings estimates. Using this historical data, I measured analyst experience. Using this matched list of analyst names in my sample with I/B/E/S analyst codes, I obtained analysts' historical first estimate on I/B/E/S, firm coverage, analyst brokerage firm, and stock recommendation history from the I/B/E/S Recommendation Detail database.

I calculated “*Analyst experience*” as the difference between the first recorded estimate the analyst made on I/B/E/S and the date of the first report by the analyst on an internet firm.

Analyst prior status*:* I measured analyst prior status from the Institutional Investor Rankings of analysts, compiling all rankings since 1972, when the rankings were first issued, through 2005. I coded the variable as 1 if an analyst had been included in the All-America Team in any of the previous years before he or she started to follow an internet firm, and 0 otherwise.

Control Variables

Analyst-related factors: Following prior studies in accounting that examine analyst accuracy (Clement, 1999; Mikhail, Walther, Willis, 2003), I controlled for analyst characteristics that might influence their recommendations of firms. I controlled for *brokerage affiliation* if the analyst belonged to the same brokerage firm that underwrote the IPO. I also controlled for analyst belonging to top decile brokerage firm and coded as dummy variable with value of 1 if analyst works at a top decile firm and 0 otherwise.

Firm-related factors: As IPO size and prior performance might influence analyst attention to the IPO, I controlled for IPO firm size. I controlled for firm performance by using logarithm of revenues before the firm listed for IPO. As a proxy for IPO firm size, I controlled for logarithm of firm assets prior to the IPO. I also controlled for IPO related factors that might influence a firm’s stock market performance. I controlled for the firm type (B2B or B2C type of internet firm). I also controlled for venture capital backing using a dummy variable of 1 if the IPO received venture capital funding prior to IPO and 0 if otherwise. Data on the number of venture capital backing and underwriters was collected from the SDC New Issues Database. I also controlled for lead underwriter reputation using Loughran and Ritter's (2004) IPO underwriter reputation ranking.

Finally, I controlled for the dot-com bubble period by coding the IPO as 1 if it occurred between January 1, 1999 and March 31, 2000, and 0 otherwise (Ritter and Welch, 2002). For the analyses that control for time, I included dummy variables for year fixed-effects.

Results

Table 2 Descriptive Statistics and Correlations

	Mean	S.D.	Min	Max	Evaluative Complexity	Experience	Status	Year 1999	Year 2000	Lead Underwriter	Top10	VC Backed	Log Revenues	Log Assets	Firmtype
Evaluative Complexity	0	1	-4.4	2.7	1										
Experience	8.04	6.33	0	23	-0.07	1									
Status	0.14	0.35	0	1	-0.04	0.25	1								
Year1999	0.54	0.5	0	1	0.04	0.03	0.07	1							
Year2000	0.17	0.38	0	1	-0.07	0	-0.02	-0.5	1						
Lead - Underwriter	0.02	0.14	0	1	-0.02	-0.01	0.01	-0.01	-0.01	1					
Top10	0.57	0.5	0	1	0.01	0.02	0.1	0.03	-0.01	0	1				
VC Backing	0.77	0.42	0	1	-0.02	-0.06	-0.01	0.07	0.03	-0.01	0.03	1			
LogRevenues	1.43	0.66	0	3.7	0.05	0.06	0.01	0.1	0.08	-0.04	0.02	0.13	1		
LogAssets	1.83	0.68	0	3.9	0.03	0.03	0.02	0.2	-0.04	-0.04	0.03	0.24	0.77	1	
Firmtype	1.24	1.00	0	3	0.01	0.04	0.07	0.18	0.03	-0.02	0	0.19	0.25	0.26	1

Table 2 presents the means, standard deviations, and correlations for dependent, independent, and control variables. The correlation between experience and status of analysts in my sample is 0.25, which implies that experience is not highly correlated with status among the analysts that followed internet firms. On average 14% of analysts in my sample have high-status. Experience and Status are negatively correlated with evaluative complexity.

Evaluative Complexity Variable

I measured evaluative complexity, comprising of the three component indicators of differentiation, specificity, and uncertainty, for each analyst report. Pairwise correlations between the three components are presented in Table 3 below:

Table 3 Pairwise Correlations of Components of Evaluative Complexity

	Differentiation	**Specificity**	**Uncertainty**
Differentiation	1		
Specificity	0.197	1	
Uncertainty	0.464	0.14	1

These correlations are significant at the $p<0.001$ level.

These are preliminary indicators that the three components of evaluative complexity are coherent and not highly correlated with each other. As a further validation of this construct, I plan to attest the scores of evaluative complexity on a randomly selected subsample of analyst reports using human coders. Comparison between the evaluative complexity scores using human coders and the above described computerized coding should provide required construct validity.

The evaluative complexity index thus constructed has a mean of 0 and a standard deviation of 1. Presented here is an example of an analyst evaluation that is one standard deviation below the mean:

> Webstakes.com's recent IPO was concurrent with those of a number of other online promotions companies. Looking at four of these companies [Mypoints.com, Freeshop.com Inc., Cybergold Inc. and Netcentives Inc.] reveals that these peers trade at roughly 40 x 2000 estimated revenues. By contrast, Webstakes.com trades at 9.7x our 2000 revenue estimate of $29 million. We believe that this disparity in valuation is unwarranted given Webstakes.com's huge market opportunity, No. 2 position in its category, unique private-label offerings and proprietary iDialog technology. Our price target on shares of IWIN is $25, offering 25% price appreciation potential from current levels.

While the above evaluation discusses the category positioning, unique technology used by the focal firm, it does not go into detail regarding how and why the peer companies were selected as the basis of the focal firm valuation. This evaluation also expresses high certainty that the focal firm will achieve growth in revenues in the near future.

Below is an example of analyst evaluation that is one standard deviation above the mean:

> We believe that it is reasonable to compare WebEx with enriched communication providers such as Raindance and Centra as well as collaboration service providers such as ACT Teleconferencing and Glowpoint. These companies all compete for the same general pool of corporate dollars and are all evangelizing the benefits of enriched communications between and within organizations. This group of companies currently trades at an average P/E of 56.8x consensus 2004 estimates and at 35.4x 2005 forecasts. By comparison, WebEx trades at only 26.2x our FY04 EPS estimate of $0.75 and at

22.3x our FY05 projection of $0.88, a significant discount to this group of small niche companies. In our opinion, WebEx is a stronger company in terms of product offering and market share, and we believe that its shares should trade at a premium instead of a discount to this group. We also compared WebEx with larger competitors that derive only a small percentage of their revenues from collaboration or enriched communication services or hardware. This group includes Microsoft and Cisco, which entered the space with their acquisitions of PlaceWare and Latitude Communications, respectively. We include rich communication and networking companies such as Avaya and Polycom in this group. This larger group trades at an average P/E of 37.8x 2004 estimates and at 27.4x 2005forecasts—again at a premium to WebEx's respective multiples of 26.2x and 22.3x. We believe that WebEx deserves somewhat of a premium to this group because it focuses solely on enriched Web-based communications, a fast-growing segment of corporate spending. As this growth accelerates, WebEx should grow faster than its larger rivals with more diverse product lines and end markets. Looking at a valuation of WebEx shares from a different angle (see Figure 5) we compare them with shares of Raindance and Polycom, two companies that most closely resemble WebEx in terms of target customers and corporate budgets. Raindance is trading at 22.5x consensus FY05 forecasts, and Polycom is trading at 27.9x our FY05 EPS number. WebEx is currently trading at 22.3x our FY05 EPS estimate, but we believe that its shares should trade at a premium to both of these companies because it has a much larger market share and growing faster than Raindance and Polycom. We also believe that when a company chooses the WebEx solution it faces fewer budget and technical hurdles than it would if it

> chose Polycom’s offering. For these reasons, we conclude that WebEx shares deserve to trade at 32x our FY05EPS estimate, putting our long-term price target at $28.

In this evaluation, the analyst provides justification behind selection of peer group companies. Here the peer group was chosen based on similarity to the focal firm in product offerings, and the target customer segment of B2B communications. The analyst also includes multiple perspectives on how the focal firm’s products compare with a diverse set of competitors. This evaluation is also not overly positive about the focal firm’s revenue growth, however it does not discuss why the focal firm’s products are superior compared to competitor’s products.

Table 4 Effect of Analyst Prior Experience on Evaluative Complexity

	Model 1		Model 2		Model 3		Model 4	
Variables	**Evaluative Complexity**		**Differentiation**		**Uncertainty**		**Specificity**	
	Coefficient	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
Experience	-0.013***	-0.004	-0.011***	-0.004	-0.011***	-0.004	-0.003***	-0.001
IPO Year 1999	0.014	-0.057	-0.007	-0.057	0.173***	-0.057	0.106***	-0.017
IPO Year 2000	-0.201***	-0.074	-0.122*	-0.074	-0.118	-0.073	0.069***	-0.022
Lead-Underwriter	-0.138	-0.168	-0.081	-0.168	0.188	-0.167	0.02	-0.051
Top10	0.029	-0.048	0.036	-0.048	-0.019	-0.048	0.007	-0.015
VC Backing	-0.068	-0.058	-0.09	-0.059	-0.187***	-0.058	-0.019	-0.018
Log Revenues	0.161***	-0.058	0.066	-0.058	0.017	-0.058	-0.003	-0.018
Log Assets	-0.082	-0.058	0.036	-0.058	0.036	-0.058	0.014	-0.018
Firm type	0.004	-0.025	0.035	-0.025	0.029	-0.025	-0.003	-0.008
Constant	0.061	-0.086	-0.058	-0.086	0.016	-0.085	0.669***	-0.026
Observations	1,774		1,774		1,774		1,774	

*** p<0.01, ** p<0.05, * p<0.1

Table 5 Effect of Analyst Prior Status on Evaluative Complexity

	Model 5		Model 6		Model 7		Model 8	
Variables	Evaluative Complexity		Differentiation		Uncertainty		Specificity	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Status	-0.177**	-0.073	-0.197***	-0.073	-0.115	-0.072	0.006	-0.022
IPOYear1999	0.015	-0.057	-0.004	-0.057	0.174***	-0.057	0.105***	-0.017
IPOYear2000	-0.201***	-0.074	-0.122*	-0.074	-0.119	-0.073	0.068***	-0.022
Lead-Underwriter	-0.123	-0.168	-0.066	-0.168	0.199	-0.167	0.022	-0.051
Top10	0.037	-0.048	0.045	-0.048	-0.014	-0.048	0.006	-0.015
VCBacked	-0.06	-0.058	-0.085	-0.059	-0.180***	-0.058	-0.015	-0.018
LogRevenues	0.153***	-0.058	0.059	-0.058	0.011	-0.058	-0.005	-0.018
LogAssets	-0.079	-0.058	0.038	-0.058	0.038	-0.058	0.015	-0.018
Firmtype	0.006	-0.025	0.038	-0.025	0.03	-0.025	-0.004	-0.008
Constant	-0.005	-0.082	-0.112	-0.083	-0.04	-0.082	0.648***	-0.025
Observations	1,774		1,774		1,774		1,774	

*** p<0.01, ** p<0.05, * p<0.1

Table 4 presents results of the ordinary least squares regression predicting the likelihood of an analyst with prior experience (before they started to follow an internet firm) expressing complexity in their justifications. Model 1 examines the effect of analyst prior experience on the *evaluative complexity* score (that is, a composite of the three components of cognitive complexity discussed above) of their justifications, with clustered standard errors (clustered around individual analysts). Models 2, 3 and 4 examine the effect of analyst prior experience on the three individual dimensions of *evaluative complexity* – differentiation, uncertainty and specificity of analyst justifications.

The results indicate that analysts' prior experience is negatively related to the cognitive complexity of their evaluations, in support of Hypothesis 1. This relationship was significant ($p<0.001$), indicating that the evaluative complexity of analyst justifications decreases as their number of years of experience increases. In addition, the results also indicate that analysts' prior experience is negatively related to all three individual components of *evaluative complexity*. This means that analysts with prior experience engaged in simpler, coarse-grained thinking regarding the underlying factors in their evaluations when compared to inexperienced analysts. The results also suggest that experienced analysts expressed more certainty in a context that is ambiguous and uncertain. Experienced analysts also focused more on the broader market-based factors and fewer firm-based attributes in their justifications of value. Based on the coefficient in Model 1, for every additional year of analyst experience, their evaluative complexity decreased on average by 0.013 or 1.3% of a standard deviation. This implies that with an increase of 1 year in analyst experience, their complexity reduced, on average, by 1.3% (because of the standardization of the evaluative complexity variable). Given the average experience of an analyst in my sample is 8 years, this suggests a decline of 10.5% in evaluative complexity, which is substantial. These results provide strong support for Hypothesis 1.

Table 5 presents results of the ordinary least squares regression predicting the likelihood of an analyst with high-status (before they started to follow an internet firm) expressing complexity in their justifications. Model 5 examines the effect of analyst prior status on the *evaluative complexity* of their justifications. Models 6, 7 and 8 examine the effect of analyst prior status on the three individual components of *evaluative complexity*. The results suggest that when a high-status analyst starts to follow an internet firm, the evaluative complexity in their justifications is lower as compared to that of a low-status analyst. The effect of analyst status on evaluative complexity is negative and this result is also significant ($p<0.001$). When a high-status analyst follows an internet firm their evaluative complexity decreased by .177 or approximately 18% of a standard deviation. This implies that on average a high-status analyst is 18% less complex in his evaluations as compared to a low-status analyst. However, when tested on the individual components of evaluative complexity score, high-status analysts did not differ significantly from low-status analysts on the components of uncertainty and specificity of their justifications. This means that analysts with prior status used fewer distinctions and contrasting viewpoints regarding the underlying factors in their evaluations when compared to inexperienced analysts. But analysts with prior status did not differ in the certainty of their evaluations and in the use of specific firm-based attributes in their justifications of value.

Interpreting results for Control Variables

It is interesting to note that the year 2000 influences evaluative complexity negatively, in the regression of analyst experience on evaluative complexity as well as the regression of analyst previous status on evaluative complexity. Considering the dotcom boom in 2000, it could be interpreted that analysts' evaluative complexity declined during this period of frenzied valuations and record number of firms going public. Furthermore, the logarithm of revenues also has a significant positive effect on analyst evaluative complexity in the above two regressions. As logarithm of revenues is a measure of firm performance before the IPOs, this implies that IPOs with proven successful financial performance garner more attention in analyst discourse as compared to IPOs that do not have positive financial histories.

Additional Analyses

Table 6 Multiple Regression with Experience and Status as Independent Variables

	Model 9		Model 10	
Variables	**Evaluative Complexity**		**Evaluative Complexity**	
	Coefficient	*Std. Error*	*Coefficient*	*Std. Error*
Experience	-0.011**	0.004	-0.011**	0.004
Status	-0.157**	-0.07	-0.157**	0.138
Experience X Status			0.007	0.011
IPOYear1999	0.017	0.057	0.018	0.057
IPOYear2000	-0.191**	0.074	-0.191**	0.074
Lead-Underwriter	-0.125	0.168	-0.126	0.168
Top10	0.037	0.048	0.036	0.048
VCBacked	-0.07	0.058	-0.066	0.059
LogRevenues	0.158*	0.058	0.157*	0.058
LogAssets	-0.079	0.058	-0.077	0.058
Firmtype	0.006	0.025	0.004	0.025
Constant	0.065	0.087	0.072	0.087
Observations	1,774		1,774	

I also ran multiple linear regression models with experience and status as independent variables and the results hold. Model 9 presents the results of multiple regression with both experience and status as independent variables. Analyst experience and status are on average negatively related to evaluative complexity and these effects are significant at the $p<0.01$ level and the effects are slightly lesser in magnitude than the standalone regressions. With each additional year of experience, evaluative complexity decreases by 1.1%. The results of this model suggest that an analyst with 8 years of previous industry experience is, on average, approximately 9% less complex in their evaluations. Similarly, a high-status analyst is, on average, approximately 16% less complex in their evaluations as compared to a low-status analyst.

Model 10 presents the results of the multiple linear regression with experience and status as independent variables, with the addition of the interaction between analyst experience and status. The interaction term is positively related to the evaluative complexity but is not significant. I also conducted additional analyses using alternative measures of specificity (using the total count of words indicating firm-based justifications and controlling for the total count of words indicating market-based justifications) and the results remained consistent.

Themes from Investor Interviews

In addition to the archival data on analyst reports, I collected qualitative data in the form of interviews of two sell-side analysts and seven buy-side analysts. Buy-side analysts provide advice for varying types of funds, ranging from mutual funds to hedge funds, and the advice often serves as a direct input to investment decisions taken by these funds. Similar to sell-side analysts, buy-side analysts vary in their experience in following new and established industry categories. One of the key sources of information that buy-side analysts use for investment decisions comes from sell-side analysts and their reports.

These interviews comprise an exploratory qualitative component of my dissertation and their purpose is to address specific alternative explanations of the effect of experience on evaluative complexity, to interpret the results of the quantitative analyses and to assess whether investors value in-depth analysis by sell-side analysts. The insights from these interviews also help me explore possible new interpretations of the results and generate potential new directions for future research.

The buy-side analysts interview questionnaire was comprised of both closed-ended and open-ended questions (Appendix 3). The closed-ended questions were asked mainly to validate certain assumptions underlying my interpretation of the empirical findings – I asked the interviewees whether they value in-depth analyses in sell-side research, and I also asked specific questions about the three components of evaluative complexity, that is, whether they valued firm-specific information, presentation of multiple viewpoints in analyses and communication of uncertainty in sell-side research. I also asked the interviewees if they paid more attention to reports by either experienced analysts or high-status analysts as compared to reports by novice or low-status analysts. I also asked open-ended questions on what elements of the analyst reports they find useful and how do they distinguish good analyst research from the rest.

These interviews lend additional corroboration for my interpretation of the main results and provide additional insight into mechanisms that underlie the empirical findings. One important insight was that experienced sell-side analysts who followed firms in established industries are trained to appear confident and sure about their evaluations. This could be a potential additional reason as to why experienced analysts display more certainty in their reports, even when following firms in a nascent industry category. Another important insight, both from the sell-side and buy-side interviews was that the focus of analyst reports differs in established and nascent industries – in that, the relevant financial metrics in established industries are historical in nature while those in nascent industries are future-oriented. One sell-side analyst mentioned:

> The kind of things that you pay attention to when you follow an established industry are typically dividends, stock buy-backs etc. But when you follow a new and emerging sector, you need a completely new orientation, often looking to the future.

Another sell-side analyst mentioned that:

> Of course, some of the skills are transferable, but you do have an embedded bias when you have worked in a previous industry.

These insights mean that sell-side analysts who followed a previous industry, either because of their training or because of their routines of evaluation, reflexively apply these routines when following firms in new industries. This could imply that experienced sell-side analysts are used to apply backward-looking metrics in prior industries and because of reliance on schema-based processing, are likely to use such metrics even when following new industries. Furthermore, a potential reason for in-depth evaluations by novice or low-status sell-side analysts could be that they are trying to establish their credibility among investors by including a wider range of informational cues in their reports. Another reason could be that experienced or high-status analysts can provide the most relevant information in an abstracted form, thus making their reports seem less detailed as compared to reports by novice or low-status analysts. The interviews lend partial support for these alternative explanations. Buy-side analysts mentioned that they value in-depth research on new technologies by sell-side analysts, which is inconsistent with the alternative explanations, but also sometimes look for expert reports when investing in new technologies.

Below are a few common themes from the interviews:

1. Buy-side analysts look for different inputs from sell-side analyst reports in established and new industries.

A common observation from all the interviews with buy-side analysts is that they look for different types of input from sell-side analysts depending on whether they are investing in established or new industries. In established industries, the buy-side understands the underlying business models and processes, as well as the competitive positioning of the firms in the industry. As a result, they mainly look for new updates on the incumbent firms such as mergers and acquisitions, stock buy backs and divestitures. Financial parameters that they look for in the sell-side research include earnings revisions, free cash flows, and dividends.

In new industries, buy-side looks for themes and narratives from the sell-side to make sense of the new technology or industry. They use the sell-side research to understand the underlying business processes and applications of the new technology, as well as how the new technology might evolve. They typically look for future projects in such industries or a long-term view of the technology and pay lesser attention to current profits or losses in the new industries. Financial parameters that they look for in such industries include addressable market, growth, and capital expenditures. Particularly interesting in the context of a new industry is that the buy-side mainly looks at sell-side research from smaller brokerage firms, as the smaller firms are usually the first ones to follow a new industry. As one analyst explained:

> Let's say I am learning about a new company or technology that I have not heard before, I have not covered before, then I pull a bunch of reports. Let's say, I want to learn about cloud infrastructure or 5G and I want to know what actually is happening in the industry. Then I pull up the Bernstein report that is in-depth and see, what are they talking about? Where do they think the technology is going? So I use that as a foundation, because then when I call the company directly, the Bernstein report gives me a background and then I use it to verify if what I read is correct or not.

Analysts who had worked in other industries prior to following internet firms are used to the "jargon" of established industries such as profits and dividends and are likely to use similar evaluative criteria to assess firms in nascent industries. Investors, on the other hand, know that the nascent industries might not be profitable in the initial years and thus focus on understanding important aspects of the new technology, relying on in-depth sell-side research to make sense of the new technology.

Further, in established markets, as investors are aware of the incumbents, in-depth reports are not necessary for their investment decisions. Experienced analysts who are used to producing cursory reports in established industries are likely to stick to the same style of research and analysis in new industries. As novice analysts do not have a prior schematic for the types of reports, they are more likely to provide comprehensive reports that go into detail about the new technology, which can help investors' perceptions of the new technology.

2. <u>Nuance is always welcome.</u>

In established as well as new industries, buy-side looks for more than the estimates in sell-side reports. They mainly look for the nuance behind the numbers. A buy-side analyst who followed established industries said:

> A good report is one that actually can get the nuance out of what's going on. With the management team, beyond the numbers, everybody can read the numbers, but beyond the numbers, what's new, what's going on in the company and it's going to make people actually reassess their positions.

Beunza and Garud (2007) looked at analysts' roles as framemakers, which goes beyond their perceived role as providers of information on publicly traded firms. Financial analysts act as storytellers that provide a narrative around the valuations of firms (Damodaran, 2017). These examples show that investors look for interpretation of the numbers from the sell-side research and that providing a good model of valuation often is not of primary value to the investors.

> I want to just be able to read a document without like having to go back and this and that, and like, think about math, like just read it once through and understand the narrative and then, look at the numbers.

3. <u>Sell-side analyst recommendations rarely matter to the buy-side.</u>

A common theme among all the buy-side analysts interviewed, both from established and new industry categories, was that, for multiple reasons, they do not pay attention to the buy, sell, hold recommendations of the sell-side analysts. First, buy-side analysts are aware that sell-side analysts do not typically issue sell recommendations. Research in accounting (Mikhail, Walther

& Willis, 2007) has shown that analysts typically issue buy or hold recommendations due to a conflict of interest (Agarwal and Chen, 2008). Second, sell-side analysts sometimes issue positive recommendations to maintain good relationships with the firm management, as this is an important input in their analysis (Brown et al., 2015) and investors value sell-side analysts' access to firm management. One portfolio manager said:

> I don't think they're meaningful at all. And I just tend to, I don't even care what their rating is. I'm really looking for, does the analyst know what they're talking about, did they do a good job of raising the issues and do they do a good job of qualitatively assessing whether they think management can grow the firm in the future?

4. <u>Buy-side analysts appreciate when sell-side conveys caution</u>.

Buy-side analysts mentioned that they specifically look for cautionary information in sell-side reports as this type of information is helpful to them in forming distinctive investment strategies. Moreover, as buy-side analysts typically follow hundreds of firms, cautionary information helps them focus on particular stocks in their portfolio:

> They definitely do pay attention to the red flags. And in fact, it's not, it's not so much on the long-term for the new technology, but it's definitely on the short to medium term because the sell-side analysts are pretty good about sensing when near-term headwinds are increasing or decreasing on, as it relates to their own model because if the sell-side go back to the number of stocks they're covering. If the number of analysts following a stock is fewer, I think that's really relevant that you should be very aware of headwinds

and tailwinds. And so you get more cautious or less cautious. I can be on the buy-side covering a hundred stocks that are in alternative energy. And so those people sell-side are very important. So I would say the degree of caution red flags is very relevant to a buy-side sentiment.

5. New industries provide opportunities for novice analysts to showcase their talent.

In established industries, buy-side analysts know which sell-side analysts are good based on their historical performance in the accuracy of their estimates, their access to the firm management, and their industry knowledge. In new industries, buy-side analysts are not sure that experienced analysts are necessarily better than novice analysts. Apart from the buy-side looking at different types of analyses from the sell-side (research on the new technology, future prospects of the industry), firms in the new industries are also initially covered by a fewer number of sell-side analysts (as compared to firms in established markets).

In summary, these interviews support the main predictions while providing additional potential explanations for cursory evaluations by experienced and high-status analysts. In established industries, experienced and high-status analysts' credibility is established, and the buy-side analysts know which sell-side analysts are reliable. Hence the buy-side analysts pay attention to the experts in established industries. However, in new markets, buy-side analysts do not rely solely on expert reports. Thus, novice and low-status analysts can gain investor attention in new markets by providing comprehensive research that is useful for buy-side analysts.

Chapter 5 Discussion, Limitations and Future Directions

Discussion

This study investigates the cognitive antecedents of analysts' justifications in the empirical context of internet technology emergence. Using a large, hand-collected data set on analyst reports, I adopt a cognitive-linguistic perspective to examine how analysts' prior experience and status influence the complexity of their justifications. The findings suggest that experienced analysts express lesser complexity in their justifications as compared to inexperienced analysts. Specifically, the findings support the argument that experienced analysts might use fewer firm-specific factors and rely more on market attributes in their justifications. In doing so, experienced analysts might be paying lesser attention to unique firm strengths in their justifications and relying more on broader market characteristics. In addition, experienced analysts might be considering fewer perspectives in assessing nascent firms leading to less-thorough analyses as compared to inexperienced analysts. In a new market context with significant uncertainty, analysts with more experience might also be conveying greater surety than novice analysts. Similarly, the results suggest that high-status actors might rely on prior cognitive schemas in their evaluations of internet firms, leading to less complexity in their evaluations compared to low-status analysts. This implies that high-status analysts might be not be considering as many viewpoints in their analyses of nascent firms compared to low-status analysts.

This research extends theory on managerial and organizational cognition by theorizing two distinct mechanisms relating to actors' reliance on schema-based processing. Experienced analysts might rely on schema-based processing because of the routines they developed through experience. In addition, high-status actors might rely on schema-based processing because of positive reinforcement through status conferral, leading to cognitive inertia of their schemas.

This research also extends theory on infomediaries by focusing on the connection between infomediaries' prior histories and the structure of their justifications. Prior research in strategy and organizational theory has paid little attention to the role of infomediaries' prior experience or status in their decision making. While some research in accounting describes the influence of experience from a traditional learning perspective (Clement, 1999; Mikhail, Walther and Hills, 2003), I adopt a more contemporary behavioral theory lens to explain the effects of experience and status on analyst evaluations. While research in accounting literature examines the effect of analyst experience on accuracy of evaluations and industry knowledge (e.g., Clement, 1999), I explore the effect of analysts' prior experience and status when they transfer to a new industry. While experienced actors might have well-developed domain-specific cognitive schemas, they may be inflexible in updating these schemas to suit evaluations of firms in new markets. Counterintuitively, inexperienced actors might engage in exploratory searching for appropriate justifications of value, guided by contextual cues. These findings also indicate that individual responses to uncertainty can be different for experienced and inexperienced actors—while experienced actors rely on prior cognitive schemas as cognitive shortcuts, inexperienced actors might rely on distant search in the absence of readily available solutions.

Contributions and Implications

This research contributes to our understanding of analyst discourse by studying the structure and content of analyst justifications. As reflected in the investor interviews, the structure and content of analyst reports are often more important to buy-side investors than the recommendations and ratings. Furthermore, looking at the structure and content of evaluations gives us important insight into why analysts' evaluations of firms in new industry categories might vary. First, although analysts apply financial models and valuation techniques that are seemingly rational and objective, the criteria and inputs that go into these financial models are likely to be influenced by analyst cognitive styles and hence could be subjective. Experienced analysts who are cursory in their evaluations of the new firms and the new technology might classify them into pre-existing established categories. As Beunza and Garud (2007) argue, analysts' classifications of new firms influence the selection of their comparable peers and the valuation techniques used to evaluate these firms. As nascent firms often lack resources and are less likely to have positive profits, their comparison to incumbent firms in established categories might paint them as less competent in the investors' view. Secondly, varied types of justifications (firm-based and market-based) enable analysts to be more agentic in their use of justifications to support firms with high valuations, in new as well as in established markets. Specifically, through usage of market-based justifications, analysts might attribute poor firm performance to market characteristics, thus mitigating negative investor focus on management.

Exploratory search for evaluation criteria by inexperienced analysts, in the absence of previously developed schemas, might lead to the inclusion of new measures for firm evaluation in new markets. In turn, this might lead to more appropriate, industry-specific criteria being included in analyst reports. Valuing new markets might require evaluation criteria that take into consideration the novelty of the underlying technology and firm-specific characteristics like customer strategy, product pipeline, and business models needed to succeed in the new market. By incorporating a "bottom-up" approach to valuations, inexperienced analysts might introduce evaluation practices appropriate for new markets. Inclusion of new evaluative criteria is important for investors to understand the business models of the new industry category. As one buy-side analyst noted:

> Every company reports revenue, gross, profit operating income, all that stuff. But, to understand business fundamentals, all the other stuff is more helpful, right? I can tell you, for Facebook, the way, pretty much everybody models this company is they look at user DAU, so daily or monthly active users, they multiply it by an average revenue per user and that's how they get to revenue. So, revenue is like a GAP requirement and that's always going to be there, but without that extra detail, you're kind of left in the dark. Like revenues of 20%, is that because more people are using it, is it because they're monetizing better? Or is there a further layer of monetization? Is it because the price per ad impression is higher? Or is it because there are more ad impressions? Is it engagement—more people spending more time seeing more ad impressions? Or, is it better advertising data or, just more better advertising investment, whatever it is. So, I think that stuff is really important actually. It's all important, but like, it would be very opaque if we didn't have these metrics.

According to March (1991), experienced actors have more knowledge, but their knowledge might be redundant in new contexts as they are less likely to engage in exploration and their knowledge might be already reflected in established rules and norms of practice. On the other hand, inexperienced actors are more likely to engage in innovative practices as they rely less on established rules and norms. Inexperienced actors' deviation from established norms might introduce innovation in the practice and criteria for evaluation, especially in new market contexts.

This research also calls attention to the paradox of the role of experience among infomediaries by developing a broader theory based on the context of the early internet industry. While infomediaries are expected to have experience in order to accurately evaluate firms, their prior experience might lead them to use evaluation criteria in reflexive ways, which ultimately can influence the legitimation of new markets and the firms therein. In applying prior evaluative schemas automatically to new markets, experienced analysts might be paying lesser attention to distinctive features of firms and relying more on casual observations of market trends. Such simplistic evaluations might lead to over-valuations or under-valuations of firms in new markets. On the other hand, inexperienced infomediaries might be flexible and experimental in their evaluations of firms in new markets, as they are more likely to consider the information in the new market context. Given that simplistic application of evaluative schemas based on other industries might lead to an underdeveloped understanding of the new technology and the new firms, these findings have important implications for new market contexts.

Past research in strategy has shown that analysts face substantial difficulties in their evaluation of firms that follow new technological strategies. Analysts may be unable to assess when established firms in an industry follow new technological strategies (Benner, 2010; Benner and Ranganathan, 2017), they may have difficulty evaluating firms when their own expertise does not match a particular firm's strategies (Zuckerman, 1999; Feldman, Gilson and Villalonga, 2014), and they might undervalue firms that follow unique strategies (Litov, Moreton and Zenger, 2012) or offer novel products (Theeke, Polidoro and Fredrickson, 2018). Although these studies examine analysts' difficulties in following incumbent firms' technological strategies, we still know little about why and how analysts' cognition plays a role in their evaluations. This study addresses this theoretical gap by investigating the analyst characteristics that might lead to either schema-based or context-based information processing. Examining the cognitive antecedents of analysts' evaluations also furthers our understanding of how analysts interpret novel technologies.

Another aspect of this research examines how status conferral is a potentially important antecedent of cognitive complexity. While there can be many positive implications of status conferral, mainly because it serves as a signal of quality to external audiences (Podolny, 1993), this research examines how status can have potentially negative implications for the comprehensiveness of evaluations of nascent firms in new market categories. There could be important additional implications of the finding that high-status actors are superficial in their evaluations of nascent firms. As external audiences might consider high-status actors more legitimate than low-status actors, their evaluations could carry more weight in shaping audience perceptions of nascent firms. Moreover, low-status analysts could also potentially follow the evaluative styles of high-status analysts, especially in new markets where evaluative criteria are still evolving.

Finally, from the standpoint of institutional theory, there has been a growing interest in studying the role of actors in the reproduction and change of existing institutions (Lawrence and Suddaby, 2006). Institutional actors can bring about institutional change based on purposive actions using power and strategic resources (e.g., Greenwood and Suddaby, 2006) or technical and market leadership (e.g., Garud, Jain, Kumaraswamy, 2002). This view of individual action in institutional contexts leads to an overemphasis on agency on the part of the actors. Critics of this view argue that due to bounded rationality, institutional actors are limited in their envisioning and enactment of institutional change while being part of that very institution (Battilana, Leca and Boxenbaum, 2009). The alternative view—that institutional change can take place without intentionality on the part of actors—has been less explored, apart from a few studies (e.g., Westphal and Park, 2012). In my research, I argue that actors can exhibit boundedly rational agency in which actors enact institutions through purposive action but rely on schemas and scripts in doing so. My research extends the view that boundedly rational analysts bring assumptions from prior experience following firms in other industries into new market contexts like the internet industry, thereby shaping practices in these new contexts without intending to do so.

Limitations

There are many possible limitations to the current research. This research pertains to the context of new markets in the initial stages of market emergence when the role of security analysts is prominent in shaping meaning making. In this stage, managers may have less influence over analyst justifications because of the uncertainty and ambiguity in these environments. Furthermore, the firms themselves—which tend to be small in new markets—are also less likely to exert influence on the analyst narratives and justifications. In established markets, however, with larger firms, managers might potentially influence the evaluations of security analysts through various symbolic means. The implications of this research thus might not be relevant to later stages of market emergence where analysts' agency in shaping shared understandings is often less influential because audiences are less reliant on analysts to make sense of market attributes.

This research also does not consider the role of other information intermediaries in audiences' sensemaking of new markets. Media and critics might also be powerful actors who influence how audiences understand new market contexts. Given that analysts are a primary source of information for other intermediaries in new market contexts—such as the media, which feature analysts' opinions in their stories (Brauer and Wiersema, 2018)—there may be an important relationship to examine between the various information intermediaries who influence meaning-making in the early stages of industry emergence.

Measuring cognitive processes behind analyst evaluations through the use of word count has certain drawbacks. For instance, some scholars argue that measuring appearance of words without considering the context in which they appear may not yield accurate reflections of the underlying intent of the word usage. However, given the alternative of human coding of text data, which has its own limitations, computerized content analysis is better suited in the current research context. Firstly, computerized content analysis allows us to examine large bodies of text data, such as examining ~2000 analyst reports, each consisting of 40 pages on average, which might prove to be expensive and time consuming when using human coders. Secondly, applying a structured inductive process to arrive at a list of keywords that are more pertinent to the context allows us to follow a middle path, where the context of the keywords is taken into consideration and at the same time a computerized analysis of the content can be conducted.

While the mechanism proposed here is that experience or status lead analysts to rely on schematic information processing, there could be alternative mechanisms that impact complexity of their evaluations. Finally, this research does not provide insights into the normative implications of evaluative complexity. While the concept of complexity and its applications is an evolving topic of interest for management scholars, further research needs to be conducted to throw light on how complexity influences investor perceptions of new technologies. The investor interviews conducted highlight that complexity is beneficial for them in the early stages of new industry evolution to understand intricate aspects of the new technology. At the same time, some investors did mention that verbose analyst reports might not be useful once the new technology becomes mainstream. These limitations could be explored in future research, and I discuss further potential explorations of this research in the next section.

Future Directions

This research examines the effects of analysts' experience and status on the complexity of their evaluations. Extending the current research, I plan to include additional dimensions of experience as moderator variables, such as the number of industries the analyst followed before following an internet firm and the distance between the internet and the previous industry.

The analyst evaluative complexity measure developed here can be extended to study top management teams' cognitive processes in the context of strategic changes or industry shocks through their communications with external stakeholders. It could be hypothesized that leaders differ in their understanding and interpretation of industry shocks, which can affect the adaption of firms to the evolving changes. Examining the complexity of leaders' communications with stakeholders can shed light into the cognitive processes behind leaders' adaptation to environmental changes. Another potential application of this perspective is to see how CEOs' previous industry experience influences their strategic decision-making when they move to a nascent industry. As discussed earlier, industry contexts shape how actors think about strategic issues. For instance, in established industries where business models are well-established and there is relatively less uncertainty, leaders pay attention to strategic issues such as mergers and acquisitions, product expansions and divestitures. By contrast, in nascent industries, business models are evolving and thus leaders focus on strategic issues dealing with industry evolution, such as matching products with customer needs, establishing product novelty among audience, and exploring and testing revenue streams. Applying the concept of complexity developed here, future research can explore the differences in the complexity of issues considered by leaders in established and nascent industries. Another possible direction for study could be to test how leaders' experiences working in a previous industry influences their cognitive complexity when they assume leadership roles in nascent industries.

The concept of evaluative complexity can be extended to various contexts involving evaluations. One such context is the venture capital industry, where investors assess new ventures based on their future growth potential. Venture capitalists could differ in the complexity of evaluations depending on their previous experience and status. Future research could explore how experienced and novice venture capitalists differ in their evaluative complexity and the implications of such evaluations on entrepreneurial firms' success. Future research could also explore how evaluative complexity of assessors varies at different stages of industry lifecycle. It could be hypothesized that in nascent categories investors adopt more complex evaluative criteria to assess new ventures, and that as the industry is stabilized the complexity of evaluations is streamlined to a few factors specific to the industry in question.

More broadly, there is a growing interest in management research to understand the cognition-language linkages and how they impact decision-making. Given that the structure of actors' language reflects their thought patterns, this lens can be used to study how cognitive antecedents such as status, power, and experience can impact actors' interpretation and depiction of the information environment. This research examined the influence of actors' status on their evaluative complexity—future research can extend this finding to explore how recency of status attainment can influence the evaluative complexity of analysts.

The current research can also be extended to study how security analysts can influence investor sensemaking of new technologies through inclusion of non-GAAP metrics. As investors try to understand the underlying business models of a new industry category, non-GAAP metrics might throw light on different types of revenue streams enabled by the new technology. For instance, in the initial stages of the internet industry some analysts used a variety of metrics—such as online traffic, unique visitors, page impressions, views per day, monthly active users, or daily active users—to help investors get a sense of the different revenue streams that could be possible in the new industry context, such as subscription revenue and advertisement revenue. As these revenue streams were specific to internet firms, the new metrics help investors make sense of the new technology and its potential growth trajectory and future applications. These non-GAAP metrics could then potentially influence investor perceptions of the new industry category.

Conclusion

New markets are "unstable, incomplete, and disjointed conceptual systems" (Rosa et al., 1999) where information intermediaries can play an important role in reducing information asymmetry between new firms and their audiences. This study extends theory to how analysts' prior histories shape their interpretation of new markets, as reflected in their discourse. In doing so, this study calls attention to the structure of analysts' discourse and the variability of their justifications. As key mediators between firms in new markets and their audiences, analysts' complexity of evaluations and the structure of their discourse can impact audiences' perceptions of the new markets in the initial stages of market emergence.

Appendices

Appendix 1 Examples of Firm-based and Market-based Justifications in Analyst Reports

Extract 1: “We are focusing on Verity because we believe that its strong product offering in a lucrative E-Sales segment, continued revenue growth and execution, and potential for category expansion make it an excellent investment vehicle. We rate the shares of Verity a BUY for growth oriented investors. We believe that the valuation divergence will dissipate over time as Verity executes on its E-Sales vision and product strategy.”

Extract 2: “The Internet is quickly evolving from a best-effort communications network to a resilient delivery system relied on by countless e-business customers and service providers. Extreme Networks is one of the companies enabling this transition by providing high-performance networking products at competitive price points. The company’s core business continues to trend well as evidenced by recent third quarter 2000 results. Products based on its latest “Inferno” chipset, such as the BlackDiamond and Summit 7i, continue to do extremely well. In the short term, we believe a substantial opportunity exists for Extreme as it migrates customers from competitor 3Com, which exited the layer 3 switch business. More important, we believe the company may be well-positioned to take advantage of the explosive growth in metropolitan optical networking with its newly announced Alpine platforms. Long term, the company may be well-positioned as 10 Gigabit technology becomes standardized. Considering that emerging service providers are still in the early stages of their network deployment, Extreme Networks may be in a strong position to experience dramatic revenue growth.”

Extract 3: “For guidance, we look to the multiples being afforded other markets-related companies that are similarly sensitive to fluctuations in market volumes and performance. The peers we refer to include Investment Technology Group, Knight TradingGroup, LaBranche and Co., and eSpeed in the United States. Internationally, five financial exchanges have started trading publicly in the last few years and offer another basis of comparison. These include Deutsche Borse AG, OM GruppenAB in Sweden, the Australian Stock Exchange, the Singapore Stock Exchange, and the Hong Kong Exchange. A helpful feature of all these companies is that they trade within a relatively tight band of P/E multiples based on 2001 earnings.”

Extract 4: “In addressing its current valuation, we examined the group within the context of a universe of Internet stocks as well as among themselves. We believe Lycos is a premier company because it is the momentum leader on the Internet, it should continue to expand its market share and improve its brand recognition, and revenues should increase at a three-year rate of 87%. As a result, we believe Lycos deserves a higher multiple than its peer group. We believe that current multiples may not be inappropriately high, given the difficulty of accurately modeling exponential growth and the fact that potentially premier companies such as Lycos could grow at sustainably higher rates, particularly in view of the 300% CAGR that we expect for advertising dollars on the Web.”

These statements show two qualitatively different justifications for valuation of firms – while extract 1 and 2 are based on firm-based justifications, extracts 3 and 4 are based on market-based justifications. In extract 1, the analyst focused on the firm’s product offering and execution that lead to firm growth. In extract 2, the analyst focused on differentiating the firm within a high-growth category based on its products and pricing strategy. These two extracts focus on heterogeneity between the firms in the market category and mention competition to claim distinctiveness of the firm’s product and customer strategy from its rivals. Extract 1 and 2 also predict firm growth based on the firm’s current products and execution.

Extract 3 and 4 focus on the homogeneity of the firms in the new market by suggesting similarity of actions, growth and effect of market forces on the firms in the new market. Extract 3 focuses on competition to point to the effect of market fluctuations on similar other firms, thereby claiming that fluctuations in firm performance should be attributed to market volatility. The analyst does not focus on the firm’s unique products or strategy in his justification for firm valuation. In extract 4, the analyst predicts future growth of the firm based on industry affiliation and not on firm-specific strengths. Competition is mentioned in extract 3 and 4 as way to justify the valuation or collective growth of the industry and not to differentiate between firms within the same industry.

Appendix 2 Codebook for Content Analysis

Category	Description	Keywords	Examples from analyst reports
Justification based on firm-based attributes	Analyst statements that indicate a positive relationship between distinctive firm attributes or comparative advantages of the firm and valuation of the firm	Management, execution, strategy, operations (excluding operating margins), product, RandD, Revenue	"Early results in its first eight markets (collocation rollout, market share gains, access line growth) show management is executing very well, reinforcing our confidence in the business model" "In our opinion, the stock price of Commerce One should continue to rise as the company executes its strategy, announces additional MarketSite portal relationships, and gains meaningful transaction revenue in its MarketSite trading communities."
Justification based on market-based attributes	Analyst statements that indicate a positive relationship between market characteristics, attributes and valuation of the firm (without focusing on firm attributes)	Market growth, lifecycle, internet penetration, industry-growth	"Digital Insight is participating in an industry that should flourish with the growth of the Internet. Less than ten percent of the 22,000 community financial institutions with assets under $10 billion currently offer an Internet banking solution. Yet, we believe that over the next several years this penetration rate will increase to 50% as community financial institutions adopt Internet banking for strategic and defensive purposes. Companies like Digital Insight should be a direct beneficiary of the industry growth." "A straightforward approach to valuing DoubleClick is to consider the company in relation to the size and growth of the larger online advertising marketplace. As online media grows and attracts increased advertising revenue over time, DoubleClick may be able to grow even more quickly than the overall average."

Appendix 3 General Open-Ended Questions for Interviews with Buy-Side Analysts

1. What do investors value in an analyst report?
    a. In-depth analysis of firm strengths and weaknesses
    b. Focus on financial aspects of the firm
    c. Focusing on the overall market category
    d. Inclusion of nuanced understanding of the firm and its products
    e. Stock recommendations
2. What are some of the key elements of that distinguish a good analyst report?
3. In your opinion, does in-depth analysis by the analyst lead to a better-quality reporting?
4. How would you tell that an analyst has done a detailed analysis in his report?
5. What information do investors look for when planning to invest in IPOs?
6. What information do investors look for when planning to invest in a new technology?

I. Three dimensions of evaluative complexity

1. To what extent do you believe that incorporating alternative scenarios will increase the quality of the analysis? (including different viewpoints)
2. To what extent do you believe that including on likelihood of different outcomes is important to the quality of the analysis? (expressing uncertainty)
3. To what extent do you believe that focusing on firm-specific strengths (vs generic market trends) will increase the quality of the analysis?

II. Importance of experience vs informational content in the analyst reports

1. When investing in a new IPO, how important are the following attributes of a sell-side analyst in your decision to use information he or she provides?

    a. Analyst’s industry experience
    b. Analyst’s *Institutional Investor* ranking

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